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*How Sleep Matters:  
Associations of Sleep with Negative Affect, Health Perceptions, and  
Cognitive Performance in Older Adults' Daily Lives*

presented by  
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*“If sleep does not serve an absolutely vital function, then it is the biggest mistake  
the evolutionary process has ever made.”*

Prof. Emeritus Allan Rechtschaffen



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## Abstract

Sleep is crucial for well-being, health, and cognitive functioning both from day-to-day and in the long-term. Because older adults experience declines in health and cognitive functioning as well as changes in sleep characteristics it is especially important to understand the interplay between sleep and daily well-being and functioning in this age group. The distinction between sleep quality and sleep duration should also be considered as their associations with daily functioning may differ. Using a broad theoretical approach to daily functioning, I thus examined daily associations of sleep quality and sleep duration with affective, health-related, and cognitive functioning in old and very old age.

In this dissertation, I used data from two seven-day experience sampling studies with young-old and old-old adults. In addition to reporting on their sleep quality and sleep duration each morning, participants rated their current emotions and stress experiences, reported their momentary health and pain, and participated in two trials of a working memory task six times per day.

Using these data, I first tested theoretical predictions that sleep is linked with affective stress reactivity rather than negative affect per se. Multilevel structural equation models (SEM) based on data from 325 older adults showed that after nights with lower sleep quality people reported more stressor-unrelated negative affect but not stronger stress reactivity the next day. However, when people experienced increased stress reactivity during the day, they reported lower sleep quality the following night. Sleep duration was not significantly linked with affective experiences.

Second, I aimed to clarify the previously indeterminate temporal direction of associations between sleep and health perceptions. Partially confirming the predictions, results from dynamic SEM based on data from 170 older adults showed that when participants slept better than usual, they reported less pain and increased self-rated health the next day. Sleeping longer was not linked with either pain or self-rated health. Regarding the reversed direction, on days when people rated their health better, they slept better, but not longer, the next night.

Third, I examined links of sleep with initial levels, learning improvements, and variability in working memory across a week and analyzed whether variations in sleep and working memory were linked from day to day. Results from multilevel location-scale models based on data from 160 older adults showed that people who slept longer and people who slept shorter than the sample average showed lower initial performance levels, but a stronger increase of working memory performance over time (i.e., larger learning effects), relative to people with average sleep duration. Sleep duration did not predict performance variability over one week. Sleeping shorter than usual was only linked with worse next-day working memory performance for people with short average sleep durations. Individual differences in sleep quality were not significantly associated with initial

performance levels, learning effects, or variability of working memory in daily life. The associations between sleep and daily functioning did not systematically differ with participants' age.

Finally, I integrate the results for the different areas of daily functioning, consider the strengths and limitations of the current research, and give an outlook of avenues for future research, including suggestions for interventions. In summary, the results from my dissertation underline that sleep is highly relevant for daily functioning in old age, and that it is important to distinguish between sleep quality and sleep duration. The results suggest a critical role of sleep quality for affective well-being and health perceptions, whereas sleep duration may be more important for cognitive performance. Overall, sleep may be a promising target for interventions to improve older adults' daily lives.

## CHAPTER 1

### General Introduction

As humans, we spend about 30% of our lives sleeping. That is a lot of time which cannot be spent on other worthwhile endeavors. Sleep researcher Allan Rechtschaffen famously said “If sleep does not serve an absolutely vital function, then it is the biggest mistake the evolutionary process has ever made.” Although research has not yet found the one vital function of sleep he was talking about, theorists and empirical researchers agree that sleep serves many important functions. To simplify and only name a few of those functions, while we sleep, our bodies allocate energy to repair and recovery (Mignot, 2008; Schmidt, 2014; Villafuerte et al., 2015) and our brains remove waste (Lewis, 2021; Shokri-Kojori et al., 2018). Furthermore, our brains process emotional information (Goldstein & Walker, 2014), and neurons restructure to enable cognitive plasticity and learning (Gorgoni et al., 2013; Walker & Stickgold, 2006).

On a larger scale, sleep is considered an important factor for public health (Chattu et al., 2018; Hale et al., 2020). People who do not get sufficient sleep report poorer mental well-being, worse physical health, or lower cognitive performance in cross-sectional studies (Devore et al., 2016; Liu et al., 2018; Lo et al., 2016; Steptoe et al., 2008). Longitudinally, people who reported insufficient sleep at an earlier point in time, were also more likely to develop mental illnesses or physical illnesses in the following years (Baglioni et al., 2011; Chaput et al., 2013; J. A. Lee et al., 2016; L. Li et al., 2021; Neckelmann et al., 2007; Sun et al., 2018). Applying this knowledge to adult development, sufficient sleep could be a predictor for successful aging.

Successful aging has recently been summarized as comprising the domains of health, physical and cognitive function, psychological adjustment and affective functioning, and active engagement with life (Fernández-Ballesteros, 2019; Urtamo et al., 2019).<sup>1</sup> Aspects from most of these domains have already been linked with sleep (Gordon et al., 2021; Liu et al., 2018; Steptoe et al., 2008) and, for example, insufficient sleep in mid-adulthood has been suggested as a predictor of cognitive decline and a risk factor for developing dementia in old age (Scullin & Bliwise, 2015; Wennberg et al., 2017). Thus, it might be of particular importance to study associations with sleep in old age. Furthermore, as people age, their sleep changes (Boulos et al., 2019; Buysse et al., 1991) and especially when moving from the third age (young-old age, ca. 65-79 years) to the fourth age (very old age, > 80 years) people tend to experience marked declines in broad areas such as mental,

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<sup>1</sup> The concept of successful aging has been criticized for inconsistent choices of included constructs, for its individualistic focus, and for ignoring the subjective meaning of successful aging (e.g., Katz and Calasanti, 2015). In their recent works, Fernández-Ballesteros (2019) and Urtamo et al. (2019) aimed to consolidate previous definitions and considered common critiques, resulting in these overarching domains. In this dissertation, I thus use the term *successful aging* to refer to maintained health, physical and psychological functioning, and overall well-being in old age.

physical, and cognitive functioning (P. B. Baltes & Smith, 2003) which might also make them more vulnerable to potential effects of insufficient sleep in daily life.

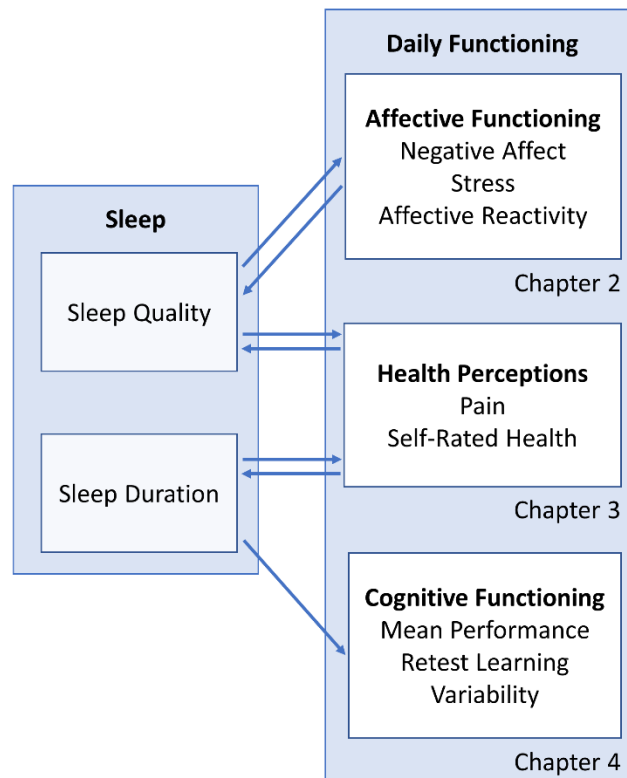
This is important, because in addition to predicting long-term developments, sleep can have very real consequences in day-to-day life. When people sleep poorly or very little at night, they can experience decreased well-being and worse cognitive function the next day (Blaxton et al., 2017; Gamaldo et al., 2010; Gerhart et al., 2017; but also see Dzierzewski, 2012; Garcia et al., 2014). Additionally, the associations between sleep and daily functioning may go both ways, that is what people experience during the day could also influence how well they sleep at night, although corresponding evidence is less consistent (Åkerstedt et al., 2012; Alsaadi et al., 2014; Konjarski et al., 2018; Krause et al., 2019; Sin et al., 2020; Slavish et al., 2018). To address how day-to-day variations in sleep are linked with short-term variations in daily functioning, it is necessary to gather such information repeatedly as people go about their daily routines. In this dissertation, I thus used momentary assessment data to analyze associations of sleep and daily functioning in older adults' daily lives.<sup>2</sup> Using a broad theoretical approach to daily functioning, this dissertation focuses on affective, health-related, and cognitive functioning (see Figure 1.1 for an overview of how daily functioning will be covered in this dissertation). These facets of daily psychological functioning cover important domains of successful aging and are crucial for the maintenance of desirable levels of well-being in old and very old age.

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<sup>2</sup> I am the sole author of Chapters 1 and 5 of this dissertation, whereas Chapters 2 to 4 are based on papers written with co-authors. For reasons of consistency, I use the personal pronoun "I" in Chapters 1 and 5 when referring to Chapters 2 to 4 as well.

**Figure 1.1**

Overview of the Domains of Daily Functioning Covered in the Chapters of this Dissertation.



## 1.1 Approaches to Studying Sleep

Sleep can be scientifically defined as a “circadian state characterized by partial or total suspension of consciousness, voluntary muscle inhibition, and relative insensitivity to stimulation” (American Psychological Association, n.d.). Sleep, its antecedents, and its consequences can be studied in diverse ways. In the next sections I will give a brief overview of three main approaches to researching human sleep and discuss age differences.

### 1.1.1 Manipulating Sleep Duration

Researchers have studied the effect of sleep by recording what happens when people do not sleep at all (sleep deprivation) or only sleep predetermined restricted amounts of time (sleep restriction). Sleep deprivation negatively affects broad areas of functioning, including affective and cognitive functioning (Killgore & Weber, 2014; Lim & Dinges, 2010; Tomaso et al., 2021; Watling et al., 2017) as well as health perceptions such as pain (Schrimpf et al., 2015). Sleep deprivation research helped identify possible mechanisms explaining the effects of sleep loss on different areas of functioning, for example, using fMRI to identify differences in brain activation when people were sleep deprived vs. well-rested. Testing affective functioning after sleep deprivation, research

identified decreased frontal control over amygdala activation to predict worse mood and increased affective reactivity to emotional stimuli (Motomura et al., 2013; Yoo et al., 2007). Regarding pain sensitivity, sleep deprivation caused increased activation in the primary somatosensory cortex as well as decreased activation in areas known to evaluate and regulate pain (Krause et al., 2019). When sleep-deprived participants worked on cognitive tasks, activation in frontal and parietal regions was increased, indicating greater effort needed to perform the task (Drummond et al., 2005). These findings stress the importance of sleep for neurological processes associated with affective, health-related, and cognitive functioning as suggested by theoretical considerations (Goldstein & Walker, 2014; Gorgoni et al., 2013; Mignot, 2008; Walker & Stickgold, 2006).

Sleep deprivation research has also considered the possibility of age differences: Some studies have indicated that sleep deprivation or restriction affected older adults less negatively compared with younger adults, for example regarding emotional and cognitive function (Adam et al., 2006; Duffy et al., 2009; Schwarz et al., 2018). However, this line of research typically compared younger with older adults and may have overlooked possible differences between young-old and old-old adults (P. B. Baltes & Smith, 2003).

Additionally, it is not directly possible to draw conclusions from sleep deprivation studies regarding effects of normal daily variations in sleep. Thus, although sleep deprivation research has elucidated important consequences of sleep loss, sleep deprivation is not representative for most people's everyday sleep experiences, and one might question its ecological validity.

### **1.1.2 Polysomnography and Sleep Actigraphy**

Alternative to preventing people from sleeping, it is possible to meticulously measure what happens in people's bodies while they do sleep. The most encompassing measurement of sleep is polysomnography which is usually conducted in a sleep laboratory and includes measures of brain activity (electroencephalography), muscle activity (electromyography and electrooculography), heart rate (electrocardiography), movement, breathing, and oxygen saturation in the blood (Kline, 2013). With data obtained from polysomnography, it is possible to identify different sleep phases, differentiating between Rapid Eye Movement (REM) and non-REM sleep, which can be further decomposed into lighter and deeper sleep stages (Kline, 2013).

Based on psychological studies using polysomnography, researchers have, for example, found that REM sleep is critical for processing emotional memories (Goldstein & Walker, 2014). Studies also identified that people with chronic pain differed from a healthy control group in some sleep parameters: they took longer to fall asleep and spent more time awake during the night (Blågestad et al., 2012). Even though many sleep laboratory studies include a first night for people to get used to sleeping in an unfamiliar environment, the experience will likely still deviate from

their everyday routines and might interfere with typical sleep architecture (Byun et al., 2019; Le Bon et al., 2001).

Sleep actigraphy, as a less invasive measurement, can be used unobtrusively in people's home environments. Actigraphy is typically recorded using small devices worn on the wrist; these so-called actigraphs can be worn across several days and nights as people go about their usual routines. Actigraphy relies on measuring people's movements with measurements allowing calculations of bedtime, wake-up time, nightly awakenings, and sleep phases with high alignment to results from polysomnography (Lehrer et al., 2022). Research found some evidence that daily experiences may predict aspects of actigraphy-assessed sleep. For instance, higher stress predicted lower sleep efficiency and longer times awake during the night in one study (Åkerstedt et al., 2007) and shorter total sleep time in another (Yap et al., 2020).

Sleep parameters obtained from polysomnography and actigraphy also change across the lifespan. A recent meta-analysis of polysomnography parameters across the lifespan found that with older ages, people tend to take longer to fall asleep, wake up more often, sleep less efficiently, and sleep shorter in total (Boulos et al., 2019). Similarly, a meta-analysis of age differences in actigraphy parameters found that older adults tend to sleep shorter but here the evidence for lower sleep efficiency was inconsistent (Evans et al., 2021).

### **1.1.3 Self-Reports**

Finally, researchers can ask people about their own sleep. Such self-report measures often focus on longer periods of time. Two of the most often used self-report sleep questionnaires, the Pittsburgh Sleep Quality Index (PSQI) and the Insomnia Severity Index (ISI), ask about the last month or the last two weeks respectively (Fabbri et al., 2021). The PSQI includes questions on sleep quality, timing, efficiency, and disturbances, as well as the use of sleep medication and daytime disturbances (Buysse et al., 1989) that are combined into one global sleep quality score. The ISI includes questions regarding difficulties falling and staying asleep, sleep satisfactions, and daytime impairment (Bastien, 2001). Alternative to these comprehensive questionnaires, self-reports can focus on fewer aspects of sleep, e.g., typical sleep duration or general sleep quality (Lallukka et al., 2018; Lo et al., 2016; Snyder et al., 2018). Using self-report assessments, cross-sectional analyses showed that people with generally better sleep quality and adequate sleep duration experience more positive mood, less pain, better health and perform better on cognitive tasks (Lo et al., 2016; Simoes Maria et al., 2020; Stewart et al., 2011; J. Zhang et al., 2012).

Self-reports of sleep also show changes across the lifespan. Considering scores on the PSQI, healthy older adults had lower overall sleep quality compared with younger adults (Buysse et al., 1991). Older adults also reported going to bed and waking up earlier than do younger adults (Buysse

et al., 1991). Additionally, many older adults reported difficulties falling asleep and experienced disrupted or non-restorative sleep (Foley et al., 1995; Newman et al., 1997). However, such sleep problems may not be a necessary consequence of aging per se but are likely associated with health issues that become more frequent with older ages (Foley et al., 2004).

Interestingly, self-reported sleep quality does not readily align with specific sleep parameters obtained from polysomnography or actigraphy; only 11-17 % of variance in self-reported sleep quality could be explained by actigraphy sleep parameters (Kaplan et al., 2017). Nonetheless, self-reported sleep is associated with important outcomes, often more so than actigraphy sleep parameters (e.g., Konjarski et al., 2018; O'Brien et al., 2011, but also see Cavuoto et al., 2016). Taken together, these findings may suggest that self-reports of sleep quality are a summative evaluation of one's sleep that is relevant for daily functioning but is not necessarily associated with specific objective sleep parameters.

Of course, people can also report how their sleep varies from night to night. To assess these variations, keeping a sleep diary is considered the gold standard (Carney et al., 2012). In sleep diaries, people record information such as their bedtime, wake-up time, sleep onset latency, total sleep time, number of awakenings, subjective sleep quality or similar aspects of the previous night's sleep for several days (Åkerstedt et al., 1994; Carney et al., 2012). The two main sleep characteristics researchers typically consider in daily life are how well and how long people sleep – *sleep quality* and *sleep duration*. To most appropriately assess day-to-day associations, it is necessary to also record antecedents or consequences of sleep as they occur in daily life, a common approach for which is using ecological momentary assessments (EMA).

## **1.2 How to Study Associations With Sleep in Daily Life?**

The main aim of EMA is to assess life as it is lived. EMA studies include repeated assessments of the constructs of interest over time and across different situations as participants go about their daily lives to increase ecological validity (Shiffman et al., 2008). The repeated assessments allow for assessing short-term variations and dynamic associations, within and across days, in different areas of functioning (e.g., Flueckiger et al., 2017; Schilling et al., 2022; Shing et al., 2012).

In EMA studies, everyday sleep is typically recorded using sleep diaries and/or actigraphy. In the following chapters of this dissertation, I focus on short-term variations in self-reported sleep quality and duration. As mentioned previously, in EMA studies conducted in daily life, associations of self-reported sleep with psychological variables are often more consistent than those with actigraphy (e.g., Konjarski et al., 2018; O'Brien et al., 2011). Therefore, analyzing daily self-reported sleep seems a promising approach to advance insights into the interplay between sleep and daily psychological functioning.



Similar to sleep quality and sleep duration varying from day to day, people's daily experiences and their level of functioning varies in their everyday lives as well and sleep may explain some of these everyday variations (e.g., Blaxton et al., 2017; Gamaldo et al., 2010). In turn, research also showed that people's daily experiences can influence both their subsequent sleep quality and sleep duration (Abeler et al., 2021; Åkerstedt et al., 2012). Accordingly, one should also assess to what extent short-term variations in daily experiences are associated with subsequent sleep – that is, one should consider bidirectional effects. Because research points to some differential associations of sleep quality and sleep duration with daily functioning (Bin, 2016; Gamaldo et al., 2010; Konjarski et al., 2018; O'Brien et al., 2011), both of those sleep characteristics should be considered.

Considering daily variations in sleep may matter in old age as well, particularly for very old adults. Whereas some previous research has indicated that older adults may be less vulnerable to effects of sleep loss compared with younger adults (Duffy et al., 2009; Ready et al., 2009; Schwarz et al., 2019), this effect may not continue into late old age. Because of advancing declines in functioning, the older people become, the more vulnerable they could be to effects of insufficient sleep in different areas of functioning. Old-old adults may have fewer cognitive and physical resources available to deal with daily demands (P. B. Baltes & Smith, 2003; Charles & Luong, 2013) so that a further reduction of resources through insufficient sleep could mean that they experience steeper decline in daily functioning following insufficient sleep. At the same time, weakening circadian rhythms and declining health with older ages have both been linked with sleep disturbances and may additionally imply increased vulnerability of sleep to daily experiences (Ancoli-Israel et al., 2008; Foley et al., 2004; Vgontzas et al., 2003).

Finally, day-to-day associations in daily life may grow into long-term developments, potentially explaining why insufficient sleep is linked with long-term detriments in mental and physical health and cognitive function (J. A. Lee et al., 2016; Spira et al., 2014; Sun et al., 2018). Consistent with this idea, people who reacted with more negative affect (NA) to sleep loss, developed more health conditions across eight years (Sin et al., 2021). Similar effects have been found for other daily associations: Repeated stronger affective reactivity and slower recovery after experiencing stressors in daily life has likewise been associated with decreases in mental and physical health over the following years (Leger et al., 2018; Piazza et al., 2013).

To summarize, in this dissertation I assessed bidirectional links of sleep quality and sleep duration with affective functioning, health perceptions, and cognitive functioning. These three domains of functioning have been linked with sleep both in the short- and long-term and their short-term links with sleep could thus be relevant for successful aging.

### 1.3 Differential Links with Sleep Quality and Sleep Duration?

In the following, I will focus on sleep quality and sleep duration as the sleep characteristics most typically considered in daily life. Sleep quality is a subjective, summative judgement of how well one has slept, whereas sleep duration refers to the time actually spent asleep. Sleep quality and sleep duration are usually moderately positively correlated (Krystal & Edinger, 2008), but they are not redundant and may show unique associations with daily functioning. To illustrate, even if someone spends eight hours per night in bed, they could experience problems falling asleep, they may frequently wake up and/or have trouble falling asleep again, or their sleep may feel unsatisfactory or nonrestorative to them.

So far, research has typically considered links between sleep quality and mental or emotional outcomes whereas sleep duration has mostly been associated with health-related and cognitive outcomes (Bin, 2016). However, in recent years, research has increasingly supported associations of sleep quality with health outcomes as well (e.g., Gadie et al., 2017; Lallukka et al., 2018), indicating that common and differential effects of sleep quality and sleep duration should be assessed. In the next sections, I summarize previous research on daily links between sleep and affective, health-related, and cognitive functioning. In doing so, I focus on open questions regarding each domain and consider differential results concerning links with sleep quality vs. sleep duration as well as potential age differences.

#### 1.3.1 Affective Functioning

Research has linked both sleep quality and sleep duration with daily emotional experiences, such as experiencing more NA or more intense stress (Åkerstedt et al., 2012; Konjarski et al., 2018). However, theoretical and experimental work suggests sleep is likely linked with reactivity to stressors rather than NA or the mere experience of stressors more generally. Insufficient sleep is thought to reduce emotion regulation capacity and therefore increase affective reactivity rather than generally impacting affect (Babson & Feldner, 2015; Goldstein & Walker, 2014; Gruber & Cassoff, 2014; Vandekerckhove & Wang, 2018) which could explain the previously mixed results when affective reactivity was not considered (Konjarski et al., 2018). In Chapter 2 of this dissertation, a person's overall daily NA is thus decomposed into the level of NA reported in situations without previous stressors – in the following referred to as *baseline NA* – and their *affective reactivity*, operationalized as the increases in NA associated with the experience of stressors (Bolger & Schilling, 1991; Sliwinski et al., 2009).

Regarding the opposite direction of effects, some studies found that higher NA predicted lower sleep quality the next night (Gerhart et al., 2017; Slavish et al., 2018), but others found no such association (e.g., Bouwmans et al., 2017; for a review see Konjarski et al., 2018). Similarly, using

emotional reactivity as a proxy for emotion regulation, it seems likely that affective reactivity rather than baseline NA or stressor occurrence could predict subsequent sleep (Babson, 2015; Espie, 2002; Fairholme & Manber, 2015; Vandekerckhove & Wang, 2018).

To date, research that addressed differential links between sleep, NA, and affective reactivity has produced mixed results. Research conceptualizing affective reactivity as the person's increases in NA associated with increases in stress intensity found that sleep quality predicted NA at average levels of stress intensity in three out of three studies and affective reactivity in two out of three studies (Blaxton et al., 2017; Flueckiger et al., 2016). One report analyzing overall NA and different forms of reactivity in separate models found that sleep quality predicted overall NA but not distal reactivity (the increase in NA compared to a pre-defined non-stressor baseline) in three assessed data sets (Marcusson-Clavertz et al., 2022). Shorter sleep duration also predicted more baseline NA the next day, but not stronger affective reactivity in NA (Sin et al., 2020). Regarding the opposite effects of affective reactivity on subsequent sleep, one report comprising three data sets found that stronger overall NA predicted lower sleep quality in one of three data sets and that increased distal reactivity predicted lower sleep quality in two of three data sets (Marcusson-Clavertz et al., 2022). When considering sleep duration as the outcome, neither baseline NA, nor stressor occurrence or reactivity had significant predictive effects (Sin et al., 2020). Thus, it remains an open question whether sleep is indirectly linked with NA via individuals' affective reactivity to stressors, or more generally with overall daily levels of baseline NA irrespective of stressful experiences.

Among older adults higher sleep quality is associated with lower NA and vice versa (Blaxton et al., 2017; Gerhart et al., 2017; McCrae et al., 2008; McCrae et al., 2016), similar to associations in younger age groups (Konjarski et al., 2018). However, the nature of associations between sleep quality and affective reactivity has not yet been studied among older adults. Lifelong experience in emotion regulation could protect older adults' affect from external influences such as insufficient sleep (Charles & Luong, 2013; Ready et al., 2009), but this effect has not been found consistently (Wrzus et al., 2014) and likely does not persist into old-old age. On the contrary, the older people become, losses in cognitive capabilities and physical resources might challenge their emotion regulation capabilities (Charles & Luong, 2013). When insufficient sleep further reduces available resources, this could impact affective reactivity more strongly in old-old compared with young-old adults.

Overall, sleep quality seems to be more consistently associated with affective functioning than sleep duration. Thus, in Chapter 2, I focused on associations of affective experience with sleep quality. I discuss differential associations with sleep quality and sleep duration in Chapter 5.

### **1.3.2 Physical Health Perceptions**

Sleep has not only been linked with affective functioning but also with physical health as indicated by medical conditions (Itani et al., 2017; Lallukka et al., 2018) and health perceptions such as perceived pain or self-rated health (Burke et al., 2012; J. Zhang et al., 2012). Health perceptions are important to consider because pain affects many older adults (Fayaz et al., 2016; Patel et al., 2013) and self-rated health is linked with functional decline and mortality above and beyond more objective health indicators (French et al., 2012; Pinquart, 2001b).

Regarding daily life studies, there has been some research showing bidirectional links between sleep and pain, whereas daily links between sleep and self-rated health have not been well-studied. Most research in daily life supports prospective links between lower sleep quality and more intense subsequent pain (Alsaadi et al., 2014; Gerhart et al., 2017; Krause et al., 2019; O'Brien et al., 2011; Tang et al., 2012; Whibley et al., 2019). Shorter sleep duration only predicted increased next-day pain when sleep quality was not simultaneously considered (Edwards et al., 2008). In contrast, more intense pain during the day predicted worse next night sleep quality (Abeler et al., 2021; Alsaadi et al., 2014; O'Brien et al., 2011) or sleep duration (Edwards et al., 2008) only in few studies. Because of mixed previous results, the temporal order of associations between sleep and pain in daily life remains an open question.

As with pain, self-rated health varies in everyday life (Wolff et al., 2012), but previous research failed to assess links between naturalistic daily variations in sleep and self-rated health. Research on cross-sectional associations has found both better sleep quality (Burke et al., 2012; Simoes Maria et al., 2020) and moderate sleep duration (ca. 7 - 8h; Liu et al., 2018; Magee et al., 2011) to be associated with better self-rated health. However, these previous approaches have two main drawbacks. First, they typically discretized sleep measures and self-rated health (e.g., good and bad sleep, good and poor health) and second, the cross-sectional data preempt assessing the direction of effects. Thus, analyzing bidirectional temporal links with sleep and health repeatedly measured will aid in assessing the size and direction of effects.

One previous study found no evidence for age differences in associations between sleep and health in a lifespan sample (Gadie et al., 2017), but young-old and old-old adults might differ nonetheless. Late old age is associated with increasing health problems and functional decline (P. B. Baltes & Smith, 2003) which could be risk factors for increasing vulnerability of health perceptions to insufficient sleep. However, research also observed a stronger association of back pain with sleep problems for middle-aged compared with old-old adults (50-59 years vs. older than 80 years; Chaudhary & Selvamani, 2021) which would indicate lower vulnerability. Accordingly, age may be relevant in associations between sleep and health perceptions, even though the direction of effects remains unclear.

Despite more consistent links with sleep quality, it seems likely that both sleep quality and sleep duration could be relevant predictors of short-term variations in pain and self-rated health. I thus aimed to address bidirectional associations of sleep quality and sleep duration with pain and self-rated health in Chapter 3 of this dissertation.

### **1.3.3 Cognitive Functioning**

Moving on to associations of sleep with cognitive functioning, I focus on working memory (WM). WM updating, as part of the executive control functions, is considered the basis for higher cognitive operations (Baddeley, 1992; Diamond, 2013) and an important factor for general cognitive functioning in old age (Verhaeghen, 2018). Insufficient sleep is thought to reduce frontal-lobe function (Lim & Dinges, 2010) which can result in impairments in higher cognitive functions such as WM (Frenda & Fenn, 2016). Previous research has found influences of everyday sleep on mean cognitive performance (Gamaldo et al., 2010), but has rarely assessed associations with learning or performance variability (for an exception focusing on a longer period see Dzierzewski et al., 2013). However, learning and variability are also important components of cognitive performance.

Retest learning, as indicated by improvements on new tasks through repeated performance, is “a basic form of cognitive plasticity” that remains into old age (L. Yang et al., 2006, p. 372). When older adults want to keep learning new skills in old age, this kind of plasticity is central and enabling cognitive plasticity is one proposed crucial function of sleep (Gorgoni et al., 2013; Walker & Stickgold, 2006). Previous research testing sleep effects on retest learning found improvements in WM performance after periods of sleep, naps, and quiet wakefulness but not after periods of being awake and active for a similar timespan (Kuriyama et al., 2008; Sattari et al., 2019; Zinke et al., 2018). Furthermore, people improved longitudinally in a WM task across days of normal sleep but improvements were impeded by sleep restriction: the shorter the sleep duration the smaller the improvement (van Dongen et al., 2003). Influences of normal variations in nightly sleep on subsequent retest learning across several days have not yet been assessed but these associations might be important from a clinical perspective, if sleep interventions could optimize cognitive plasticity based on retest learning.

In addition to mean performance and retest learning, performance variability is an important aspect of cognitive functioning. Cognitive performance variability has mostly been seen as a risk factor and is, for example, associated with cognitive decline or mortality (Batterham et al., 2014; Lövdén et al., 2007). However, during learning (i.e., up to an asymptotic personal level of performance) variability may indicate adaptive processes (Allaire & Marsiske, 2005; Siegler, 1994). Variability in WM performance which is controlled for retest-learning improvements could thus be an important indicator for cognitive aging, beyond an individual’s mean performance.

Regarding effects of sleep, studies have documented weaker effects of sleep deprivation on cognitive performance and performance variability in older compared with younger adults (Adam et al., 2006; Duffy et al., 2009). A suggested explanation for this finding was that older adults may simply need less sleep; alternatively weakening circadian rhythms with aging could imply smaller effects of accumulated sleep loss (Duffy et al., 2009). However, it is possible, that this effect may not continue into old-old age because of increasing loss of resources and accelerating cognitive decline (P. B. Baltes & Smith, 2003; Salthouse, 2019).

In contrast to sleep duration, daily variations in sleep quality were not associated with variation in cognitive performance in most studies (Gamaldo et al., 2010; Holanda & Almondes, 2016; Zavec et al., 2020, but also see Nebes et al., 2009). Thus, I focussed on associations between sleep duration and working memory in Chapter 4 of this dissertation. I consider differential associations with sleep quality and sleep duration in Chapter 5.

#### **1.4 Dissertation Overview and Research Questions**

In this dissertation, I assess links of day-to-day variations in sleep with older adults' daily functioning. I consider three different domains that are important aspects of daily functioning: affective functioning, physical health perceptions, and cognitive performance and plasticity. I used data from two EMA studies with very similar data collection protocols. Study 1, the EMIL study, included two groups of participants: 120 young-old adults, aged 66-69 years ( $M = 67.2$ ,  $SD = 0.9$ ; 54.2% male), and 45 old-old adults aged 84-90 years ( $M = 86.7$ ,  $SD = 1.5$ ; 37.8% male). Study 2, the SOEP Couple Dynamics Study, was a couple study including heterosexual couples. To ensure independence of data from individuals, I included data from one randomly drawn partner from each couple, that is, data from 160 (50% male) individuals who were aged 61 to 88 years ( $M = 71.8$  years,  $SD = 5.8$ ).

Every day of the seven-day assessment period, participants in both studies answered up to six daily surveys on a touchscreen tablet provided to them. They completed the first questionnaire right after waking with subsequent assessments prompted to be answered at 10am, 1pm, 4pm, 7pm, and 9pm. At the first assessment each morning, participants answered questions about their previous night's sleep. In both Study 1 and Study 2 participants reported on stress experiences and momentary NA at every assessment (used in Chapter 2). In Study 1 they additionally reported momentary subjective health and pain intensity (used in Chapter 3) and completed two trials of a numeric working memory updating task at every assessment (used in Chapter 4). With these data I aimed to answer the following main research questions:

**RQ1:** *Are the links of sleep quality and sleep duration with daily affective and health-related functioning bidirectional?*

Bidirectional prospective associations with sleep have been proposed; sleep quality and sleep duration are thought to influence subsequent emotional and physical functioning and vice versa, but the findings regarding these links are mixed. Identifying the (main) direction of effects is important to determine potential intervention targets for improving daily functioning in old age.

**RQ2:** *Which different aspects of affective functioning, physical health perceptions, and cognitive functioning are associated with sleep quality and sleep duration?*

Although research has found that sleep, affective, health-related, and cognitive functioning are generally linked, several distinct aspects of those areas of functioning deserve attention because they could be differentially associated with sleep quality and sleep duration. Regarding affective functioning, theories suggest that sleep likely does not impact NA directly but indirectly through increased affective reactivity. In the area of physical health perceptions, research has focused on pain intensity, but it is also possible that sleep quality and duration are associated with more general health perceptions like self-rated health. For cognitive performance, previous research has predominantly studied influences of sleep duration on mean performance or reaction times, but we know little about learning or performance variability.

**RQ3:** *Do associations between sleep and daily functioning differ across old age?*

Despite potentially increasing vulnerability across old age and implications of sleep quality and sleep duration regarding successful aging, daily associations with sleep are understudied in this age group. If improving sleep quality or sleep duration could increase older adults' daily well-being and functioning or if intervening in people's daily lives improved their sleep, this might positively influence long-term health outcomes and successful aging even into very old age. Thus, identifying these links would be of utmost importance.

**RQ4:** *Are sleep quality and sleep duration differentially associated with daily functioning?*

So far, research has most often considered links between sleep quality and mental or emotional outcomes whereas sleep duration has mostly been associated with physical/health-related and cognitive outcomes. However, sleep quality may also be important for health, calling for more attention to differential associations.

To address these research questions, in Chapter 1, I gave an introduction to selected aspects of sleep research and establish the current state of knowledge regarding links between sleep and different areas of functioning in daily life. For Chapter 2, I pooled data from Study 1 and Study 2 to

assess whether bad sleep interferes with emotion regulation and predicts affective reactivity or whether sleep more generally predicts baseline NA. Similarly, I tested whether increased affective reactivity or baseline NA predicted next night sleep quality. Thus, I analyzed bidirectional associations (RQ1) and different aspects of affective functioning (RQ2). For Chapter 3, I used data from Study 1 to assess whether sleep predicts perceived pain and self-rated health or vice versa, thus addressing bidirectional associations (RQ1) and different aspects of health perceptions (RQ2). Furthermore, I included both sleep quality and sleep duration to find out whether one of these sleep characteristics is more closely linked with perceived pain and/or health (RQ4). For Chapter 4, I again used data from Study 1 to clarify associations between sleep and WM performance in older adults' daily lives. Specifically, I aimed to find out whether average sleep duration was linked with the initial level, retest learning (plasticity) or variability in performance across the week of the study (RQ2). Additionally, I analyzed whether daily variations in sleep duration predicted daily variations in working memory. In all three empirical chapters, participants age (Chapter 2) or age group (Chapters 3 and 4) was considered as a moderator for the associations to address potential age differences (RQ3).

To address whether sleep quality and sleep duration were differentially linked with the different areas of functioning (RQ4), for Chapter 5 I repeated the analyses regarding sleep and affective reactivity from Chapter 2 and regarding sleep and working memory from Chapter 4 with sleep duration and sleep quality respectively. In Chapter 5, I furthermore integrate and discuss the results with regard to all four research questions, considering the strengths and limitations of the current research and give an outlook of avenues for future research.



## CHAPTER 2

### Good Night – Good Day?

#### Bidirectional Links of Daily Sleep Quality with Negative Affect and Stress Reactivity in Old Age

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#### Abstract

Bidirectional links between sleep quality and emotional experiences are complex and not yet well understood – especially in old age when substantial changes occur in sleep and emotional experiences. Because previous research rarely considered the role of stressors, we examine if older adults' sleep quality is directly associated with subsequent negative affect or more indirectly via affective reactivity to stressors. Specifically, we investigate whether and how older adults' sleep quality predicts negative affect and affective reactivity to stress on the following day, and vice versa. For seven consecutive days, 325 older adults (61-90 years, 49% women) reported their sleep quality each morning as well as momentary negative affect and stressful events multiple times a day. Results from multilevel structural equation models showed that after nights of lower sleep quality, older adults reported more negative affect, but not higher affective reactivity to stressors. In turn, after days with increased affective reactivity but not more negative affect, participants reported worse sleep quality. We discuss whether older adults are able to regulate the effects of low sleep quality, but have difficulties down-regulating stress and its effects on sleep.

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## 2.1 Introduction

People commonly report that they are more easily stressed after having slept poorly, or that they sleep badly after a stressful day. Although these bidirectional links have been supported in past work (e.g., Åkerstedt et al., 2012; McCrae et al., 2008; Slavish et al., 2018), some important questions remain. First, theory and empirical results suggest that sleep is associated specifically with affective reactivity, that is the increase in negative affect that results from the experience of stressors and adversities, rather than negative affect per se (Goldstein & Walker, 2014; Gruber & Cassoff, 2014; Mauss et al., 2013; Zohar et al., 2005). However, little research has actually examined stressor-unrelated negative affect and affective reactivity to stressors simultaneously. Second, whereas many studies focus on sleep duration (e.g., Wrzus et al., 2014; Zohar et al., 2005), sleep quality, as experienced and reported by participants, appears to be more consistently linked with negative affect (e.g., Blaxton et al., 2017; McCrae et al., 2008). Sleep quality can vary tremendously despite identical sleep duration and may be linked with affective experiences in a unique way. Third, both sleep quality and emotional experiences change systematically across the adult life span and especially in old age (Ancoli-Israel et al., 2008; Ohayon et al., 2004; Riediger & Rauers, 2014) making it relevant to study associations between them within old age specifically. This study addresses these open questions through examination of time-ordered associations between daily sleep quality and negative affect, both in terms of stressor-unrelated negative affect and affective reactivity to daily stressors, using momentary assessment data obtained in two studies spanning young-old and old-old age.

### 2.1.1 *Sleep Quality Predicts Negative Affect and Affective Reactivity*

Naturalistic (as opposed to laboratory-based) sleep studies typically distinguish people's self-reported sleep quality from quantitative aspects of sleep, such as sleep duration. Sleep quality may matter particularly in older adults' daily life, because sleep quality decreases more substantially in old age than does duration (Ancoli-Israel et al., 2008), and is linked with stronger negative affect more consistently than is sleep duration (Konjarski et al., 2018). A recent review of daily life studies showed a prospective link between sleep quality and subsequent daily levels of overall negative affect, with lower sleep quality predicting higher levels of subsequent negative affect in 13 out of 15 studies examining different populations (Konjarski et al., 2018). Only three of these studies focused on older adults, with results being comparable to those of other age groups (Blaxton et al., 2017; McCrae et al., 2008; McCrae et al., 2016).

This research did not consider the experience of stressors, despite a substantial body of research showing that daily negative affect is associated with – and might be triggered by – exposure to daily stressors (e.g., Bolger & Schilling, 1991; Sliwinski et al., 2009; Stawski et al., 2019). Thus, it

is an open question whether sleep quality influences negative affect indirectly via individuals' affective reactivity to stressors, or more generally by intensifying or attenuating overall daily levels of negative affect irrespective of stressful experiences. In this study, we therefore decompose a person's overall daily negative affect into two components, namely their level of negative affect observed in situations without previous stressors – hereafter named *baseline negative affect* – and their *affective reactivity*, conceptualized as the increases in negative affect associated with the exposure to stressors (Bolger & Schilling, 1991; Sliwinski et al., 2009).

We assume that insufficient sleep may reduce older adults' resources available to manage daily stressors (Gruber & Cassoff, 2014) and, thus, may increase negative affect in response to stressors. Indeed, after nights with worse sleep quality people reported increased stress intensity in a daily life study (Åkerstedt et al., 2012). Following this rationale, several lines of conceptual work assume that sleep quality influences individuals' capability to effectively down-regulate negative affect in the face of stressors rather than sleep being linked with the occurrence of stressful experiences or individuals' baseline negative affect per se (Babson & Feldner, 2015; Goldstein & Walker, 2014; Gruber & Cassoff, 2014). Consistent with this perspective, poor sleep quality the week prior to participation in a laboratory experiment was found to predict less efficient instructed emotion regulation during the experiment (cognitive reappraisal; Mauss et al., 2013).

To date, only two publications have reported the effect of self-reported sleep quality on negative affect and affective reactivity, assessed simultaneously in everyday life (Blaxton et al., 2017, Flueckiger et al., 2016). Blaxton et al. (2017) found that sleep quality predicted both affective reactivity and negative affect. The same was true for one of two studies presented by Flueckiger et al. (2016), whereas in the second study sleep quality only predicted overall negative affect. However, in this research sleep quality predicted affective reactivity as the person's increases in negative affect associated with stress intensity and not stressor occurrence and it predicted the person's negative affect at their average levels of stress intensity, which may still include some reactivity to stressor occurrence. Taken together, these findings suggest that previously found predictive effects of sleep quality for overall negative affect might partly be due to increased affective reactivity, but this evidence is far from conclusive and more research is necessary.

Moreover, the aforementioned studies assessed negative affect and stress only on a daily rather than on a momentary basis (Blaxton et al. 2017; Flueckiger et al., 2016). However, it seems valuable to include repeated momentary measurements across the day. First, negative affect assessed shortly after a stressful situation (i.e., affective reactivity within two to three hours after stressor occurrence) is more likely to represent a reaction to a specific situation rather than overall mood or well-being following a more or less stressful day. Second, emotional experiences in the morning seem to be more closely associated with the previous night's sleep quality than emotional

experiences later in the day (Könen et al., 2016) so that time of day may be relevant to include in the analyses. In summary, we expected that older adults' sleep quality predicts daily affective reactivity to stressors rather than enhancing or attenuating the daily levels of baseline negative affect.

### **2.1.2 Affective Reactivity Predicts Sleep Quality**

Emotional experiences throughout the day may also impact next night sleep quality. First, successful emotion regulation is given a central role in a psychobiological model of good sleep developed in the context of insomnia (Espie, 2002) and a similar association is assumed for sleep in general (Babson, 2015). Second, arousal is thought to play an important role in impacting subsequent sleep. Both physiological and psychological arousal have been linked with sleep onset latency and sleep duration in the laboratory (Tang & Harvey, 2004) but research suggests a stronger link between psychological arousal and sleep quality in daily life (Tousignant et al., 2019). One of the potential pathways linking emotion regulation to pre-sleep arousal and subsequently to worse sleep could be rumination. Rumination can prolong the negative emotional consequences of stress by inhibiting effective emotion regulation (Kirkegaard Thomsen, 2006; Wrzus et al., 2015) and is associated with worse subsequent sleep (Thomsen et al., 2003). Thus, better emotion regulation could potentially be beneficial to sleep as it should be associated with shorter time periods spent dwelling on negative experiences. In this study, we consider affective reactivity as an outcome of emotion regulation and thus a reasonable proxy of the process of emotion regulation. Research shows that past-oriented rumination seems to be more consistently associated with sleep than future-oriented worry, at least in insomnia patients (Carney et al., 2010). This supports the idea that affective reactivity to past stressors during the day could be a relevant factor for next night sleep quality.

Despite theoretical suggestions that affective reactivity and not simply the occurrence of stressors or negative affect per se can influence sleep quality (Fairholme & Manber, 2015), the predictive effect of affective reactivity for sleep quality has not been studied extensively (for a recent example regarding sleep duration, see Sin et al., 2020). Studies that assessed associations of other emotional experiences with subsequent sleep quality in daily life have produced mixed results. Some studies found that higher negative affect predicted lower sleep quality the next night (Gerhart et al., 2017; Slavish et al., 2018), but others found no such association (e.g., Bouwmans et al., 2017; for a review see Konjarski et al., 2018). Besides negative affect, specific characteristics of daily stress experiences have also been examined as predictors of subsequent sleep. Specifically, stress or worries at bedtime but not earlier in the day were found to influence sleep quality during the following night in one study (Åkerstedt et al., 2012), in line with findings indicating that the mere

number of stressors experienced throughout the day did not predict sleep quality (Sin et al., 2017).

A substantial proportion of old and very old individuals faces losses in many domains of functioning that might challenge their ability to regulate emotions in the face of stressors (Charles & Luong, 2013; Kunzmann et al., 2022). Because getting over the day's stressful experiences might be the crucial aspect of the interplay of daily stressors and affect impacting nighttime sleep, it is important to understand how affective reactivity to stressors is linked with subsequent sleep quality in old age. We expected that older adults' daily affective reactivity rather than their baseline negative affect or the number of stressors they experience predicts next night sleep quality.

### **2.1.3 Age-Related Differences in Sleep Quality and Emotional Experience**

Older adults tend to sleep less deeply, less efficiently, and wake up earlier in the morning than do younger or middle-aged adults (Ohayon, 2004). Indeed, many adults aged 65+ report at least one chronic sleep problem, such as difficulty falling asleep, difficulty sleeping through the night, non-restorative sleep (56%, Foley et al., 1995), or disrupted sleep (65%, Newman et al., 1997). Yet, these problems may also be linked with decreasing health and not with age per se (Ancoli-Israel et al., 2008).

At the same time, emotional experiences change across the lifespan and in old age. For example, research has found age-related decreases in high-arousal negative affect, but increases in low-arousal negative affect in adults aged 60 and older (Pinquart, 2001a; but see Isaacowitz & Smith, 2003) and increases in negative affect at the very end of life (Gerstorf et al., 2018; Schilling et al., 2018, but see Kunzmann et al., 2000). More strongly increasing reactivity to stressors with higher age in a late life sample (66-95 years) has also been reported (Sliwinski et al., 2009), although evidence regarding age-differences in affective reactivity is mixed (see Schilling & Diehl, 2015; Stawski et al., 2019). Life-long experience in emotion regulation may increase the effectivity of at least some strategies of emotion regulation (e.g., Shiota & Levenson, 2009), but selected gains in emotion regulation may become increasingly rare in late old age (Charles & Luong, 2013). For example, old-old adults were less able to implement instructed emotion regulation to reduce negative feelings compared with young-old adults (Kunzmann et al., 2022).

Age-related changes in sleep and negative affect might also change the mutual associations between sleep quality and negative affect as people get older. Results from studies examining associations between sleep quality and negative affect among older adults (Blaxton et al., 2017; Gerhart et al., 2017; McCrae et al., 2016; McCrae et al., 2008) are similar to what has been found with younger age groups (Konjarski et al., 2018), in that higher sleep quality is associated with lower negative affect and vice versa. However, the nature of associations between sleep quality and affective reactivity among older adults is not yet known. Furthermore, previous studies did not

assess potential age effects within old age despite significant developmental changes occurring in this period potentially covering four decades (e.g., in the third age vs. fourth age; P. B. Baltes & Smith, 2003).

While it has been suggested that older, compared to young or middle-aged, adults may be less influenced by less or poorer sleep due to better emotion regulation protecting affect from external influences (Charles & Luong, 2013; Ready et al., 2009), this effect has not been found consistently (Wrzus et al., 2014) and is unlikely to persist into old-old age. On the contrary, the older people become, decreases in cognitive capabilities and possibly increasing physical vulnerabilities (Charles & Luong, 2013) may compromise emotion regulation with further reduction of resources through lower sleep quality potentially impacting affective reactivity more strongly. Similarly, it has been assumed that increasing prevalence of insomnia with age could be explained by higher vulnerability of older adults' sleep to arousal produced by stress (Hot et al., 2015; Vgontzas et al., 2003). Thus, following predictions by the strength and vulnerability integration model (SAVI; Charles, 2010; Charles & Luong, 2013), the older people become, the more vulnerable they could become to the effects of sleep on affective reactivity and vice versa. Therefore, it is important to critically assess associations between sleep quality and affective reactivity for potential effects of age.

#### **2.1.4 Health and Time of Day as Potential Further Predictors**

When examining associations between daily affect and sleep quality in old age, certain further factors that are outside the main scope of this research should be considered as covariates. For example, health, or rather illness, has important links with both sleep quality and affective well-being and is also associated with age. Many age differences regarding sleep disappear when health status is controlled for (Foley et al., 2004). Several medical and psychiatric diagnoses (e.g., cardiovascular diseases, mood and anxiety disorders) as well as the total number of comorbidities seem to be associated with sleep quality, particularly in old age (Ancoli-Israel et al., 2008; Foley et al., 2004; Hayashino et al., 2010) and could be relevant for mutual associations between sleep quality and affective reactivity. Thus, comorbid conditions should be accounted for while assessing associations between sleep quality and emotional experiences.

Furthermore, temporal aspects of associations between sleep and emotional experiences have rarely been considered in previous research, but some evidence suggests that temporal proximity is an important factor. This could mean that emotional experience in the morning is tied more closely to the previous night's sleep quality than emotional experience later in the day (Könen et al., 2016). Conversely, emotional experiences in the evening could be more closely associated with sleep quality in the following night (Åkerstedt et al., 2012; Könen et al., 2016). It is therefore

relevant to assess affect and stress across the day to examine such temporal effects of the time of stressor occurrence and affect assessment.

### **2.1.5 The Current Study**

Because most current theories expect sleep to be associated with affective reactivity to stressors rather than baseline negative affect, we examine bidirectional temporal associations between sleep quality, affective reactivity, and baseline negative affect. This study pooled data from two seven-day studies in which older adults (60-90 years) reported about their momentary negative affect and experience of stressors multiple times throughout each day and about their sleep quality each morning.

We hypothesized that lower sleep quality is associated with higher next day affective reactivity to stressful events (H1a), and that this association is stronger at older ages (H1b). Furthermore, we hypothesized that higher affective reactivity, that is, less efficient regulation of affect following a stressful event, is associated with lower next night sleep quality (H2a), and that this association is also stronger at older ages (H2b). We investigated the specificity of associations between sleep quality and affective reactivity by additionally examining associations between sleep and baseline negative affect.

## **2.2 Methods**

### **2.2.1 Transparency and Openness**

We report sample size and power considerations. Documentation on all measures assessed and analysis scripts for main and additional analyses are available at <https://osf.io/98u2s/>. We are not in a position to make data publicly available because the data contain information that could compromise research participants' consent and privacy (e.g., health information). The data presented in this study are however available in a moderated fashion from the ILSE team. Towards that end, we have established procedures in the ILSE study over the past ten and more years that we have successfully implemented numerous times. The hypotheses and analysis plan follow strong confirmatory principles but were not preregistered.

### **2.2.2 Participants**

Data were pooled from two ambulatory assessment studies that used very similar data collection protocols. Pooling of data led to a larger sample size and thus greater statistical power, compared to analyzing both samples separately. Previous research suggested that our sample size and protocol are sufficiently powered to assess effects in a three-level model: Specifically, Level 3 sample sizes of 100 or more (i.e., 100 or more participants in our case) have sufficient power to

assess random slopes at Level 2 (Jong et al., 2010; E. Lee & Hong, 2021), which are the main effects of interest here.

### *Sample 1*

The *EMIL* study (Emotional Reactivity and Emotion Regulation – A Multi-Timescale Approach Added to ILSE), is a multi-component project that included a seven-day ambulatory assessment and laboratory-based psychological testing. We used data provided by two groups of participants; 120 young-old adults, age 66-69 years ( $M = 67.2$ ,  $SD = 0.9$ ; 54.2% male) and 45 old-old adults, age 84-90 years ( $M = 86.7$ ,  $SD = 1.5$ ; 37.8% male). Most participants were married ( $n = 103$ , 62.4%), some were widowed ( $n = 30$ , 18.2%) or divorced ( $n = 22$ , 13.3%), and few were single ( $n = 9$ , 5.5%; for  $n = 1$ , information on relationship status was not provided). In total 69.7% ( $n = 115$ ) reported being in a committed relationship. On average, participants had completed 14.42 years ( $SD = 2.49$ ) of formal education. All the young-old and most of the old-old participants were recruited from the Interdisciplinary Longitudinal Study of Adult Development (ILSE; see Sattler et al., 2017), with an additional 15 old-old participants recruited from the community via advertisements in local newspapers. As described elsewhere (Schilling et al., 2022), better cognitive test performance at the last wave of ILSE (2014-2017) was the main predictor for taking part in EMIL. The project was approved by the ethics committees of the University of Heidelberg and the German Society for Psychology (DGPs) and participants provided written informed consent. Data were collected between March 2018 and August 2019 in the regions of Heidelberg and Leipzig. For this study, we only use data from the ambulatory assessment component of EMIL; for details on the complete study please see <https://osf.io/98u2s/>. Participants were compensated with €125 for full participation.

### *Sample 2*

Sample 2 took part in a couple study including heterosexual couples also participating in the Socio-Economic Panel (SOEP), a longitudinal study of a nationally representative sample in Germany (for more details, see Pauly et al., 2021). The data pooled with Sample 1 (which was not from couples) consisted only of the data obtained from one randomly drawn partner from each couple, and excluded one participant who was younger than age 60 years. Sample 2 thus consisted of 160 (50% male) individuals aged 61 to 88 years ( $M = 71.8$  years,  $SD = 5.8$ ). Most participants were married ( $n = 155$ , 96.9%), and few were cohabiting ( $n = 5$ , 3.1%). On average, participants had completed 9.91 years ( $SD = 2.43$ ) of formal education. The project was approved by the ethics committee of the Psychology department at Humboldt University Berlin and participants provided written informed consent. Data were collected in 2016–2018 across Germany. Participants were compensated with up to €100 for full participation.



### 2.2.3 Procedure

Participants from both samples were provided with and trained on the use of a touch-screen tablet (Apple iPad) on which they would complete the surveys. Five participants in Sample 1 who were not comfortable using the iPad were provided paper-pencil versions of the questionnaires. Participants had access to continuous phone support and there was a scheduled phone call on the second day in the ambulatory assessment phase to clarify any questions. Every day of the seven-day assessment period, participants answered up to six brief questionnaires on the iPad: the first questionnaire was completed right after waking (i.e., self-initiated event-based assessment), with subsequent assessments scheduled to be answered at 10am, 1pm, 4pm, 7pm, and 9pm. Based on previous work (e.g., Chui et al., 2014; Hoppmann et al., 2018; Weber et al., 2020), these 2- to 3-hour intervals were chosen as ideal to assess daily hassles/stressors and to model the circadian rhythms of salivary cortisol (not used in this study). The iPads prompted participants to fill out the questionnaire at the scheduled times, with leeway of 30 minutes before and two hours after the prompted times to accommodate participants' daily schedules.

At the first assessment each morning, participants reported on their momentary affect and then answered questions about their previous night's sleep quality. At all other assessments, participants reported on their momentary affect and then answered questions about their stress experiences (only participants in Sample 1 also answered questions regarding their stress experiences in the first assessment each morning).

In both samples, adherence to the protocol was very high: On average, participants completed reports on 6.93 ( $SD = 0.55$ ) of the 7 days and responded to 5.80 ( $SD = 0.53$ ) of the 6 assessments per day. Ambulatory assessment data included 13,313 assessments nested within 2,305 days. Information about sleep, stressor occurrence, and negative affect as used to study the links between sleep quality and next day affect was provided in 11,773 assessments (88.4%) on 2,224 days (96.49%) by 325 participants. Information to study the links between negative affect, affective reactivity and next night sleep quality was available for 1907 days by 323 participants (because sleep quality at the night following the last assessment day could not be reported).

### 2.2.4 Measures

#### *Momentary Negative Affect*

Momentary negative affect was measured at each assessment using the six emotion adjectives that were available in both studies: *angry, nervous, agitated, sad, depressed, disappointed*. The emotion adjectives included in each study were chosen because these cover different levels of arousal (Feldman Barrett & Russell, 1998) and, based on previous research, are well suited to everyday-life contexts (e.g., no/few floor or ceiling effects, within-person fluctuations, between-

person differences therein, reliable assessment; for discussion, see Brose et al., 2020). Each item was rated using a slider scale (“How ... do you feel right now?”; 0 = *not at all* to 100 = *completely*), with the slider being initially presented in the middle of the scale (i.e., at 50). To move on to the next item, participants had to move the slider. Together, the negative affect items had good internal consistencies at both the between-person level ( $\omega = .968$ ) and the within-person level ( $\omega = .812$ ). A momentary affect score was calculated for each occasion as the mean of the six item responses. In the models, this momentary overall negative affect was decomposed into baseline negative affect (in situations without a previous stressor) and affective reactivity (increase in negative affect in situations with vs. without previous stressors).

#### *Momentary Stressor Occurrence*

Following the assessment of momentary affect, participants were asked how stressed they had felt since the last assessment. Sample 1 participants answered the question, “Did a stressful situation occur since the last assessment?”, with a *yes* (=1) or a *no* (=0). *Yes* responses were probed for the category of stressor they experienced (e.g., health, financial, daily hassles). Sample 2 participants were directly asked what made them feel stressed and could indicate different categories (e.g., interpersonal, health, financial stressors) which was coded as a stressor having occurred (=1) or state that they were not stressed by anything in particular which was coded as no stressor having occurred (=0). The proportion of assessments with vs. without a previous stressor on a given day was used as a covariate in some of the analyses.

#### *Sleep Quality*

In the first assessment after waking each morning, participants reported their perceived sleep quality. They answered the question, “How was the overall quality of your sleep?” using a slider from 0 = *extremely bad* to 100 = *extremely good*. Similar single-item assessments of sleep quality have been used in previous research (see, e.g., Mauss et al, 2013; Sin et al., 2017).

#### *Covariates*

*Age.* Age was measured as the difference between participants’ birth date and the first assessment date.

*Sample.* To control for possible differences in study design, a *sample* variable was included as a covariate (0 = Sample 1, 1 = Sample 2).

*Health.* As part of comprehensive questionnaires (for details see <https://osf.io/98u2s/>), participants of both studies answered morbidity checklists and checked the presence (*yes* = 1, *no* = 0) of 15 medical conditions, including hearing impairment, vision impairment, hypertension, high cholesterol, arthritis/rheuma, heart failure, circulatory problems, diabetes, osteoporosis, cancer,

myocardial infarction, stroke, depression, dementia, HIV/AIDS. The total number of self-reported chronic illnesses was used as an indicator of *health*, with higher scores indicating poorer health.

*Time of Day.* The *time* of each assessment was logged automatically by the assessment software (or by participants completing paper-pencil versions of the questionnaire).

### **2.2.5 Data Analysis**

The multilevel nature of the data, with repeated assessments nested within days nested within people, was accommodated using multilevel structural equation models.

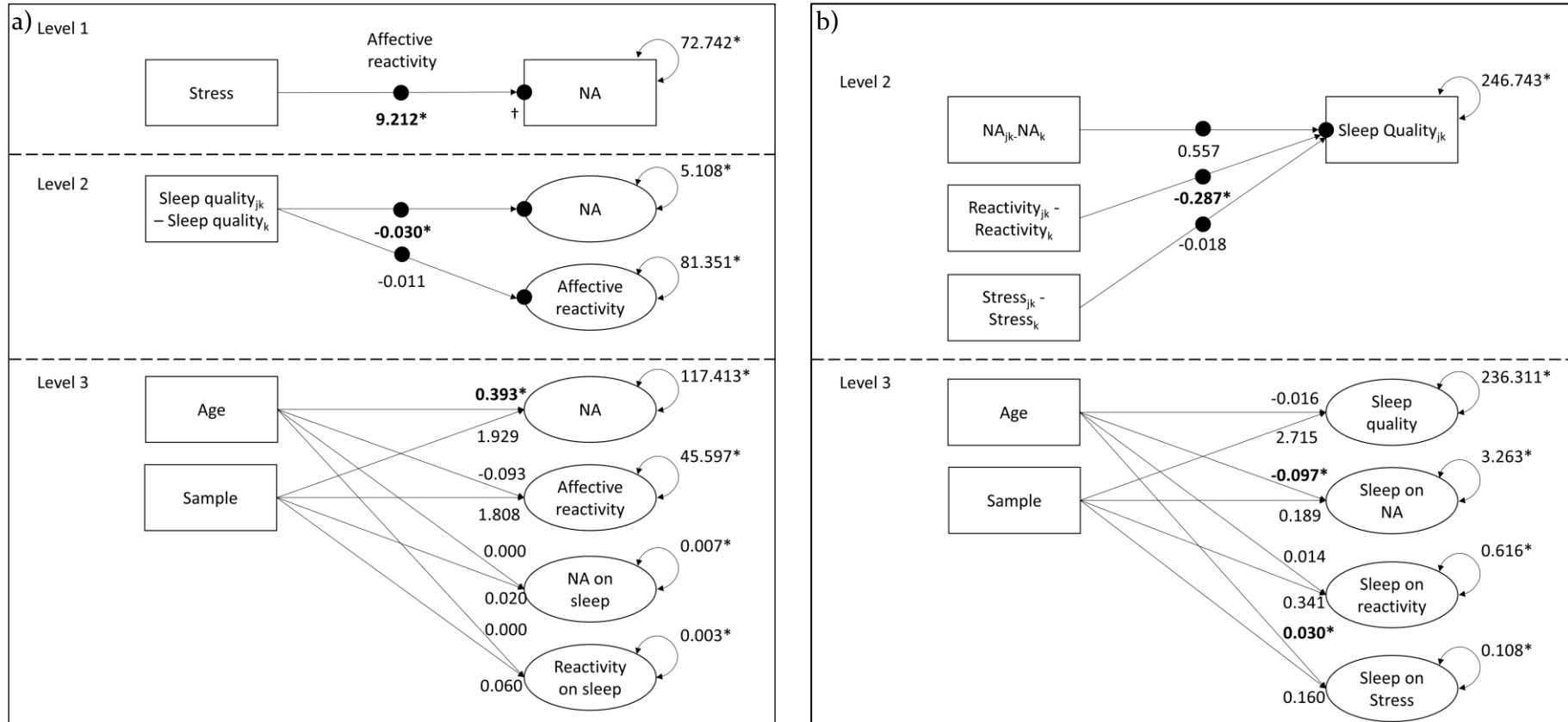
#### *Sleep Quality as a Predictor of Negative Affect and Affective Reactivity (H1a-b)*

Associations between sleep quality and next days' affective reactivity and negative affect were examined using the three-level model shown in Figure 2.1a (corresponding equations can be found in Supplement S2). At Level 1 (repeated assessments within-days) the momentary occurrence of a stressor is included as a binary predictor of momentary negative affect. The Level 1 model includes two random effects that are indicated as black dots in the figure: day-specific intercepts indicating the expected value of negative affect in moments where there was no stressor (illustrated as the black dot at the end of the arrow from stress to NA in the top panel of Figure 2.1a) and day-specific affective reactivity slopes indicating the expected increase in negative affect in moments where there was a stressor (black dot in the middle of the arrow from stress to NA).

These random effects represent latent variables and are displayed as ellipses at Level 2 in Figure 2.1a (middle panel). Latent daily within-person variation in the baseline level of negative affect (intercept indicating expected level of negative affect in moments without a stressor) and affective reactivity to stressors are then regressed on the previous night's sleep quality variable (person-mean centered). Level 2 includes four random effects (again represented by black dots): person-specific intercepts for baseline daily negative affect and for daily affective reactivity, and person-specific associations of daily sleep quality with baseline daily negative affect and daily affective reactivity. These four latent variables are then represented as ellipses at Level 3 (bottom panel of Figure 2.1a) that are regressed on Age (grand-mean centered at 72.2 years) and Sample (grand-mean centered). A model with the person-mean of sleep quality included as an additional variable on Level 3, was examined, but inclusion of this variable did not change any of the results. Thus, to keep focus on the within-person associations, we report on the more parsimonious model described here.

**Figure 2.1**

Structure of Analysis Models for Sleep Quality Predicting Negative Affect and Reactivity (a) and Negative Affect, Reactivity and Stress Predicting Sleep Quality (b), including model estimates.



Note. NA = negative affect. Manifest variables are depicted as rectangles. Random effects are indicated by black dots: Random intercepts as dots at the end of arrows, random slopes as dots in the middle of arrows. Random effects are then used as latent variables and depicted as ellipses on higher levels.

†The overall Level 1 intercept of NA was 9.573 and the overall Level 2 intercept of Sleep Quality was 70.164.

### *Negative Affect, Stress, and Affective Reactivity as Predictors of Sleep Quality (H2a-b)*

To examine how daily affective reactivity predicts next night's sleep, we used a two-step approach. In a first step we estimated the affective reactivity random slopes for each day and person in a separate three-level model, and in a second step we used these estimated scores to predict next night sleep quality. This is a strategy commonly employed in previous research (e.g., Charles et al., 2013; Mroczek et al., 2015), which sidestepped the problem that lower level random slopes (i.e., reactivity, denoting the within day slope of momentary negative affect predicted by stressor occurrence) cannot currently be used as predictors of higher level random slopes (between-day differences in sleep quality predicted by reactivity) in the same multilevel model in Mplus. For consistency, we also estimated and saved latent daily negative affect and stress estimates.<sup>3</sup> For model equations, please see Supplement S1. In the first-step three-level models, we calculated the Level 2 (between-days/within-person) means from 100 draws from the posterior distribution (i.e., so-called plausible values) of reactivity, negative affect, and stress to be used as the respective predictors in the second-step model. The estimation in the first-step model implies that the daily scores of negative affect, stress and reactivity were person-mean centered, hence representing the deviation of a particular day's negative affect/reactivity from a person's overall mean negative affect/reactivity, and for stress the deviation of a particular day's proportion of stressful situations to a person's average proportion of stressful situations per day. This stress variable was multiplied by 100 to represent percentage points.

The second-step main model examining how negative affect and affective reactivity predicted next night sleep quality is illustrated in Figure 2.1b. This model comprises the between-days/within-person and between-person levels, for which we continue using the labels Level 2 and Level 3 even though the main model does not comprise a corresponding Level 1. Level 2 (within person/between days) includes four random effects, the person-level intercept of daily sleep quality, and three random slopes – person-level associations of the previously exported reactivity slopes, negative affect, and stress with sleep quality (black dots in the upper panel of Figure 2.1b). These associations are modelled as latent variables on Level 3 and were then predicted by Age and Sample (both grand-mean centered) on Level 3, as in the previous model. For model equations, see Supplement S2.

#### *Additional Analyses Including Time of Day and Health*

In additional analyses, we included time of day and participants' number of chronic

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<sup>3</sup> Daily negative affect estimates were saved from the same first step model, that provided the latent daily reactivity estimates (i.e., the models random negative affect intercept estimates). Latent daily stress estimates were obtained from a separate first-step model (i.e., a random random-intercept-only model of the momentary stress measure).

illnesses. Time was included on Level 1 in the models for sleep quality predicting reactivity and negative affect both as a main effect and as an interaction with stress, representing a general trend of negative affect experience across the day and potential changes in reactivity across the day. Time was centered to 10am (i.e., the first scheduled assessment that most participants have filled out at the same time) to ease interpretation. For the model in which reactivity and negative affect predict sleep quality, time was included in the first-step models used to export negative affect, reactivity, and stress intercepts/slopes. Accordingly, we exported the Level 2 estimates of negative affect, reactivity, stress, general time trend in negative affect, and the interaction of stress and time predicting negative affect (i.e., time differences in reactivity) to be used as predictors in the second-step main model. For these analyses, time was centered at 9pm (i.e., the last scheduled assessment) to ease interpretation for potential proximity effects.

Because of links of health with both sleep and negative affect, we analyzed separate models including the number of illnesses as a further Level 3 (between person) predictor of the Level 2 random effects in the main models. Health was grand-mean-centered.

#### *Model Estimation and Model Fit*

Models were specified and estimated as multilevel structural equation models in Mplus (Version 8.3; Muthén & Muthén, 1998-2017) using the Bayes estimator (Markov Chain Monte Carlo with Gibbs sampler) with default diffuse priors (for details see Asparouhov & Muthén, 2010). The estimations used two chains with a minimum of 20,000 iterations (half used as burn-in; half used to compute posterior distributions). Convergence was evaluated using the Gelman-Rubin diagnostic with values close to 1 taken as a sign of convergence (Potential Scale Reduction Factor; Gelman & Rubin, 1992; B. Muthén & Asparouhov, 2012). Missing data is accommodated with full information estimation unbiased under missing at random assumptions (Asparouhov & Muthén, 2010). We approximated standardized path coefficients for the primary findings using standard deviations as suggested by Hoffman and Stawski (2009).<sup>4</sup> Code for all models (including additional analyses) is available at <https://osf.io/98u2s/>.

### **2.3 Results**

Descriptive statistics and intercorrelations of the main variables are reported in Table 2.1. On average, people reported relatively low levels of negative affect and stress as well as relatively high levels of sleep quality (Table 2.1).

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<sup>4</sup> Specifically, we calculated SDs from the Level 2 (between days/within person) variance estimates. For negative affect and reactivity these were taken from three-level models including the regression of negative affect on stress on Level 1 and Intercepts on Level 2 and 3. For sleep quality this was a two-level (Levels 2 and 3) intercept-only model.

**Table 2.1**

*Descriptive Statistics and Correlations for Negative Affect, Stress and Sleep Quality. Pooled within person correlations are displayed below and weighted between person correlations above the central diagonal.*

Variable	Mean (SD)	Average within-person SD	ICC	Correlations					
				NA	Stress	SQ prev.	SQ next	Age	Health
NA <sup>a</sup>	12.2 (12.9)	9.348	0.571	-	<b>0.511</b>	<b>-0.306</b>	<b>-0.308</b>	<b>0.191</b>	<b>0.121</b>
Stress <sup>b</sup>	0.253 (0.247)	0.334	0.289	<b>0.322</b>	-	-0.091	-0.089	<b>0.154</b>	<b>0.176</b>
SQ previous <sup>c</sup>	69.7 (16.5)	13.442	0.512	<b>-0.083</b>	<b>-0.051</b>	-	<b>0.985</b>	-0.002	-0.074
SQ next <sup>c</sup>	70.2 (16.6)	12.688	0.532	-0.016	0.002	<b>-0.174</b>	-	0.004	-0.076
Age	72.2 (7.45)	-	-	-	-	-	-	-	<b>0.410</b>
Health	2.58 (1.78)	-	-	-	-	-	-	-	-

*Note.* Correlations were calculated using the package psych (Revelle, 2021) in R Studio (RStudio Team, 2021). SQ = sleep quality. NA = negative affect. ICC = intraclass correlation coefficient.

<sup>a</sup>Scale 0-100; n = 13313 assessments. <sup>b</sup>Presence vs. absence of stressor (1/0), n = 12091 assessments. <sup>c</sup>Scale 0-100. Sleep quality was only assessed once daily, n = 2247 days (previous)/1928 days (next). Sleep quality for the next night is only available for days 1-6 and included for within person correlations as directionality is of interest here.

**Bold face** indicates  $p < .05$ .

As evident from the intraclass correlation coefficients (ICCs) and the intraindividual standard deviations, the repeated measures variables varied substantially both within and between persons.

Zero-order correlations indicate that negative affect was higher when stressors occurred—both within and between persons (Table 2.1). As expected, lower sleep quality was associated with higher negative affect. Within persons, this was only the case for the sleep quality of the previous night, but not next night. Occurrences of stress were associated within person with lower previous night, but not next night sleep quality. No significant association between average sleep quality and average frequency of stressor occurrence was observed on the between-person level.

### **2.3.1 Previous Night Sleep Quality as a Predictor of Affective Reactivity and Negative Affect**

Results from models examining the relation between sleep quality and next day affective reactivity and negative affect are shown in Table 2.2 and Figure 2.2a. First, results revealed significant affective reactivity to stress (i.e., significantly increased negative affect after stress situations compared to situations without stress, see row “Reactivity,” Table 2.2). With respect to H1a, previous night sleep quality was not, on average, associated with affective reactivity. However, higher previous night sleep quality was linked to lower baseline negative affect ( $b = -0.030$ , Table 2.2, see row “NA predicted by SQ”; in standardized form,  $\beta = -0.190$ ).

Contrary to hypothesis H1b, age was not related to differences in affective reactivity nor its associations with sleep quality. The only significant effect of age was on differences in baseline negative affect (i.e., intercepts, Table 2.2, row “Intercept NA predicted by age”,  $b = 0.393$ ). Specifically, the model parameter suggests that an individual age 82.2 years had baseline negative affect that was 3 units higher than an individual age 72.2 years. Results from a model that included between-person differences in sleep quality as an additional predictor showed a significant association between average sleep quality and average baseline negative affect, but not average affective reactivity. The substantive results reported in this section remain. The full results from this model are reported in the Supplement, Table S1.



**Table 2.2**

Results from Three-Level Models: Sleep Quality Predicting Reactivity and Baseline Negative Affect.

	Estimate	95% CI
<b>Fixed Effects</b>		
Intercept NA	<b>9.573</b>	[8.376, 10.788]
Reactivity (NA predicted by stress)	<b>9.212</b>	[8.139, 10.261]
Reactivity predicted by SQ <sup>a</sup>	-0.011	[-0.057, 0.034]
NA predicted by SQ <sup>a</sup>	<b>-0.030</b>	[-0.049, -0.011]
<i>Age and Sample as Moderators</i>		
Intercept NA predicted by age	<b>0.393</b>	[0.227, 0.559]
Intercept NA predicted by sample	1.929	[-0.496, 4.337]
Reactivity predicted by age	-0.093	[-0.231, 0.051]
Reactivity predicted by sample	1.808	[-0.335, 3.97]
Reactivity predicted by SQ x age	0.000	[-0.006, 0.005]
Reactivity predicted by SQ x sample	0.060	[-0.022, 0.139]
NA predicted by SQ x age	0.000	[-0.003, 0.002]
NA predicted by SQ x sample	0.020	[-0.018, 0.058]
<b>Random Effects (Variances)</b>		
<i>Within Person, Within Days</i>		
NA residual variance	72.742	[70.612, 74.952]
<i>Within Person, Between Days</i>		
NA residual variance	5.108	[3.607, 6.798]
Reactivity residual variance	81.351	[69.996, 93.969]
<i>Between Person</i>		
NA residual variance	117.413	[99.779, 139.116]
Reactivity residual variance	46.597	[33.528, 62.718]
Reactivity predicted by SQ residual variance	0.003	[0.001, 0.011]
NA predicted by SQ residual variance	0.007	[0.004, 0.011]
R <sup>2</sup> Level 1	0.263	

Note. SQ = sleep quality. NA = negative affect. CI = credibility interval. N<sub>Level1</sub> = 11773, N<sub>Level2</sub> = 2224, N<sub>Level3</sub> = 325.

<sup>a</sup>Sleep quality was person-mean centered.

**Bold faced** estimates indicate that the CI does not cover 0. Because variances can never be estimated at or below zero in Bayesian analysis in Mplus we did not bold face variance estimates.

R<sup>2</sup>s indicating the explained total variance on the lowest level (i.e.,  $\Omega^2$ ; Xu, 2003; corresponding to  $R_t^{2(fvm)}$  as suggested by Rights & Sterba, 2019)

### 2.3.2 Affective Reactivity and Negative Affect as Predictors of Next Night Sleep Quality

Results from models examining how daily baseline negative affect and daily affective reactivity were linked with next night sleep quality are shown in Table 2.3 and Figure 2.2b. In line with H2a, higher affective reactivity was associated with lower next night sleep quality (see row “SQ predicted by reactivity”,  $b = -0.287$ ; in standardized form  $\beta = -0.155$ ).

The extent to which baseline negative affect was related to next night sleep quality was moderated by age (Table 2.3, see rows “SQ predicted by NA” and “SQ predicted by NA x age”). We used the Johnson-Neyman procedure as implemented in Mplus (Lin, 2020) to identify the age

range where the link between baseline negative affect and sleep quality was significantly different from zero. For participants between 60 to 67 years old, the link between baseline negative affect and sleep quality was positive; for individuals in this age range, higher baseline negative affect was associated with higher sleep quality. For individuals 68 years or older, there was no significant association between baseline negative affect and sleep quality. Additionally, the extent to which stressor occurrence was related to next night sleep quality was moderated by age (Table 2.3, see rows “SQ predicted by Stress” and “SQ on Stress x age”). Here, for participants aged 60 to 63, higher occurrence of stressors was linked to lower next night sleep quality; for participants 84 years and older, higher occurrence of stressors was related to higher sleep quality.

**Table 2.3**

*Results from Two-Level Models: Reactivity, Negative Affect, and Stress Predicting Sleep Quality.*

	Estimate	95% CI
<b>Fixed Effects</b>		
Intercept SQ	<b>70.164</b>	[68.371, 71.991]
SQ predicted by reactivity <sup>a</sup>	<b>-0.287</b>	[-0.478, -0.085]
SQ predicted by NA <sup>a</sup>	0.557	[-0.228, 1.342]
SQ predicted by stress <sup>a</sup>	-0.018	[-0.196, 0.159]
<i>Age and Sample as Moderators</i>		
Intercept SQ predicted by age	-0.016	[-0.265, 0.235]
Intercept SQ predicted by sample	2.715	[-0.927, 6.376]
SQ predicted by reactivity x age	0.014	[-0.011, 0.04]
SQ predicted by reactivity x sample	0.341	[-0.054, 0.742]
SQ predicted by NA x age	<b>-0.097</b>	[-0.195, -0.003]
SQ predicted by NA x sample	0.189	[-1.322, 1.669]
SQ predicted by stress x age	<b>0.030</b>	[0.006, 0.055]
SQ predicted by stress x sample	0.160	[-0.194, 0.516]
<b>Random Effects (Variances)</b>		
<i>Within Person, Between Days</i>		
Intercept SQ residual variance	246.743	[228.591, 266.667]
<i>Between Person</i>		
Intercept SQ residual variance	236.311	[196.317, 285.282]
SQ predicted by reactivity residual variance	0.616	[0.316, 1.044]
SQ predicted by NA residual variance	3.263	[0.48, 8.311]
SQ predicted by stress residual variance	0.108	[0.014, 0.352]
R <sup>2</sup> Level 2	0.110	

Note. SQ = sleep quality. NA = negative affect. CI = credibility interval.  $N_{\text{Level}2} = 1907$ ,  $N_{\text{Level}3} = 323$ .

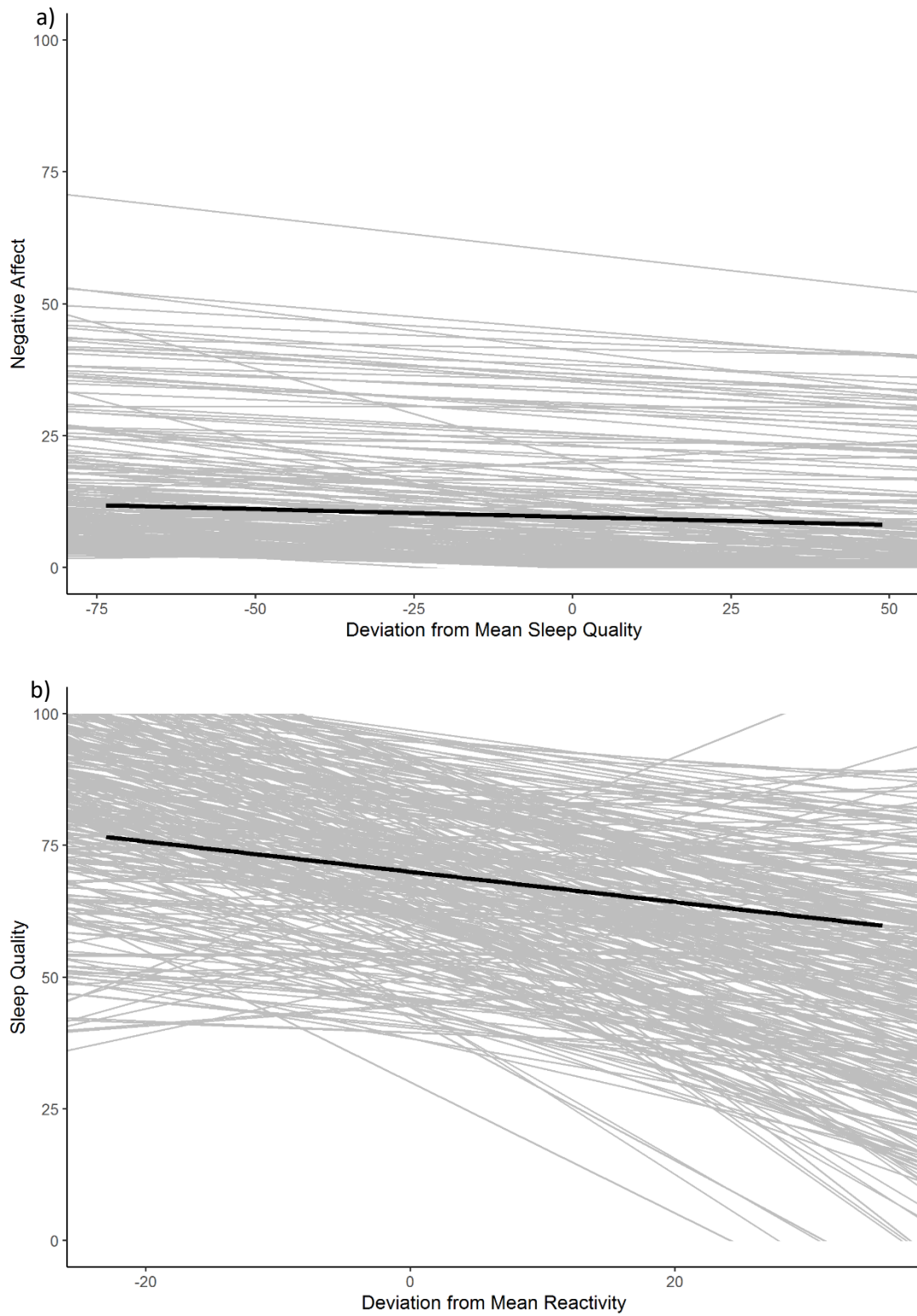
<sup>a</sup>These predictors were Level 2 estimates from separate three-level models and are de facto person-mean centered.

**Bold faced** estimates indicate that the CI does not cover 0. Because variances cannot be estimated at or below zero in Bayesian analysis in Mplus we did not bold face variance estimates.

R<sup>2</sup>s indicating the explained total variance on the lowest level (i.e.,  $\Omega^2$ ; Xu, 2003; corresponding to  $R_t^{2(\text{fvm})}$  as suggested by Rights & Sterba, 2019).

**Figure 2.2**

*Model Predicted Random Slopes Per Person and Average Slope for (a) Sleep Quality Predicting Negative Affect and (b) Reactivity Predicting Sleep Quality.*



### 2.3.3 Additional Analyses Including Time of Day and General Health

Inclusion of the time of day in the main models did not markedly alter the associations between sleep quality and negative affect (for full model results see Supplement, Tables S2 and S3). For the analyses of sleep quality predicting negative affect and reactivity, time of the assessment (in hours) was centered to the first scheduled morning assessment at 10am. Results showed that sleep quality predicted negative affect in the morning similarly to across the whole day (Supplementary Table S2 cf. Table 2). However, this effect differed between the two included studies: Simple slopes analyses indicated that when controlling for time in the model, sleep quality only significantly predicted morning baseline negative affect in Sample 1 ( $b = -0.051$ , 95% CI [-0.079, -0.023]), but not in Sample 2 ( $b = -0.005$ , 95% CI [-0.041, 0.033]). Overall, negative affect did not show a particular trend across the day ( $b = -0.012$ ) and reactivity did not change depending on the time of day either ( $b = -0.025$ ). Age moderated this effect ( $b = -0.017$ ): Among participants aged 72 years or younger the coefficient was positive, that is, affective reactivity to stressors was stronger later in the day; for adults older than 72 years this effect was not significant.

In the analyses of negative affect and reactivity predicting sleep quality the next night, time was centered to the last scheduled assessment at 9pm. The results showed that higher reactivity was still associated with worse sleep quality ( $b = -0.243$ ; Supplementary Table S3 cf. Table 2.3). Baseline negative affect shortly before going to sleep was not linked with next night sleep quality either ( $b = 0.055$ ). When taking into account time of day, the effect of age on the link between baseline negative affect and next night sleep quality was no longer significant.

The main results were also not altered when controlling for health (see Supplement, Tables S4 and S5 for full model results). Only, the effect of age on the link between negative affect and next night sleep quality was no longer significant when illnesses were included in the model.

## 2.4 Discussion

We investigated bidirectional associations between daily sleep quality and emotional experience among older participants who took part in 7-day ambulatory assessment studies. To increase statistical power and the reliability of results, we pooled two independent samples, assessed with almost identical assessment protocols. Our analyses suggest that variations in sleep quality within individuals predicted individuals' next day negative affect. More specifically, and different from our prediction, participants reported stronger baseline negative affect but not stronger affective reactivity after sleeping more poorly than usual. At the same time, in line with our hypotheses, affective reactivity (i.e., experiencing increased negative affect following stressors) predicted lower next night sleep quality. These results are summarized in Figure 2.3. Neither experiencing more stressors than usual nor experiencing stronger baseline negative affect was

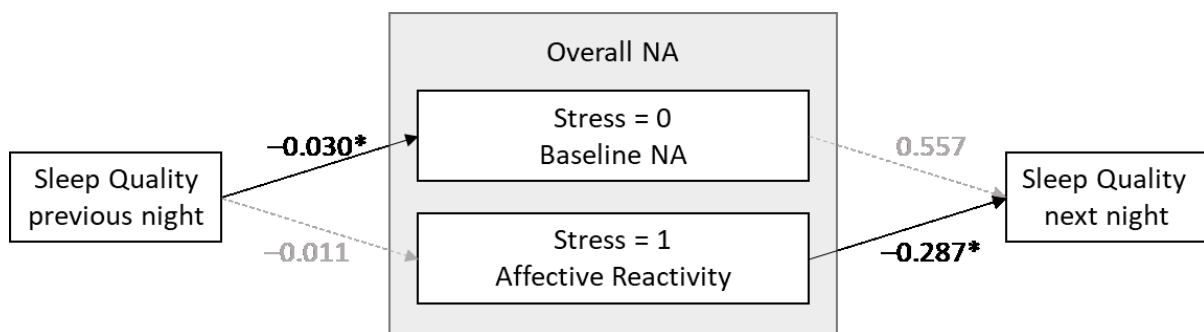
associated with next night sleep quality.

The standardized coefficients for the link between sleep quality and next day baseline negative affect as well as for the link between reactivity and next night sleep quality, albeit significant, indicate small effects. Since negative affect and sleep quality are both influenced by a multitude of factors one would expect small effects for single influences, as was the case in previous research (Blaxton et al., 2017; McCrae et al., 2008). Nonetheless, small effects are typical for studies assessing daily life and can accumulate to have important long-term effects, for example on health (Leger et al., 2018; Piazza et al., 2013).

In contrast to our expectations, older participants did not show the expected stronger associations between sleep quality and affective experiences. It may be noted, however, that the older participants were, the more baseline negative affect they reported, whereas we found no significant age differences in affective reactivity.

**Figure 2.3**

*Summary of Main Results for the Bidirectional Associations Between Sleep Quality and Negative Affect.*



*Note.* NA = negative affect. Black lines and numbers represent significant effects,  $*p < .05$ . Grey dashed lines and numbers represent insignificant results,  $p > .05$ . For full model results see Table 2 and Table 3.

### 2.4.1 Sleep Quality Predicts Baseline Negative Affect

Our results are in line with research indicating that following nights with worse sleep quality, people tend to experience more negative affect (e.g., Flueckiger et al., 2016; McCrae et al., 2008; also see review by Konjarski et al., 2018). However, in contrast to most current theories (e.g., Goldstein & Walker, 2014; Gruber & Cassoff, 2014), in the present study, sleep quality was associated with stronger next day baseline negative affect but not with stronger affective reactivity to stress. One conclusion that could be drawn is that sleep quality may only be more subtly linked with negative affect among older adults than past work suspected. Theoretical work has suggested that the effect of sleep quality on negative affect may be mediated by poor emotion regulation and

stronger affective reactivity as a result of deficits in emotion regulatory attempts (e.g., Goldstein & Walker, 2014; Gruber & Cassoff, 2014). However, results to the contrary also exist: Two publications that addressed associations of sleep quality with negative affect and affective reactivity simultaneously, consistently found predictive effects of sleep quality on negative affect, but observed predictive effects of sleep quality on affective reactivity only in two of three reported studies (Blaxton et al. 2017; Flueckiger et al., 2016). Similar results were found in a recent study assessing links between sleep and stress responses: Sleep quality reliably predicted baseline negative affect, but not reactivity – however these two aspects were not included in the same model (Marcusson-Clavertz et al., 2022). In addition, at least one other study showed that the previous night's sleep only predicted reactions to mild stressors, but not to highly stressful ones (Minkel et al., 2012). This further substantiates more subtle influences of a bad night's sleep, rather than amplifying affective reactivity. If we think of baseline negative affect as akin to mood, which exists in the background and is less consciously regulated, this may also explain why it could be influenced by subtle background variables, such as a bad night's sleep. Along these same lines, increased baseline negative affect could be a sign of diffuse discomfort following worse sleep. However, sleep might also influence different components of the emotion regulation process, such as situation selection, attention, appraisal, and responses, differently, which might explain the results (Fairholme & Manber, 2015; Gross, 1998). For example, following nights with worse sleep, older adults may choose not to expose themselves to potentially stressful situations, which is one key strength of older adults' emotion regulation (Charles & Luong, 2013).

With regard to the time of assessments, overall, we did not observe stronger associations of previous sleep quality with negative affect in the morning, contrary to previously reported results (Könen et al., 2016). However, this inconsistency with previous findings may be linked to specifics of the current study: Sample 2 did not report whether a stressor had occurred in the first assessment each morning – hence, as this important predictor was missing, these early negative affect assessments were not included in the model estimation. Because it seems likely that the influence of sleep could be more pronounced in the morning when it is unlikely that much else would have happened yet, it is possible that this effect is thus not observed. It remains to be assessed in future research whether this effect does depend on study designs (e.g., timing of assessments) or whether it may be age specific.

In contrast to our hypotheses regarding age, there were no significant age effects on the associations of sleep quality with negative affect, however due to the relatively small number of old-old adults and only cross-sectional information on age-differences this should also be addressed in future research.

### **2.4.2 *Affective Reactivity but Not Affect per se Predicts Sleep Quality***

Considering the hypothesis that emotional experiences predict next night's sleep quality, stronger affective reactivity was linked with next night sleep quality, rather than how participants felt more generally or the number of stressors they experienced in a certain day. This is in line with theoretical predictions (Babson, 2015). It seems likely that elevated baseline negative affect – which may represent something like bad mood across the day, but not elicited by specific stressors – may not be strong enough to impact next night sleep, but negative affect largely increased by stressful events can do so. These results also align with those of a recent publication which reported that affective reactivity but not baseline negative affect predicted subsequent sleep quality (Marcusson-Clavertz et al., 2022). A possible explanation for this could be that stronger affective reactivity may be linked with rumination and pre-sleep arousal, for example because in the evening people could still be more preoccupied with events that affected them more strongly during the day. This is supported by the fact that mere occurrence of more stressors than usual during the day did not predict worse next night sleep quality, in the current or previous studies (e.g., Sin et al., 2017). However, this reasoning remains speculative here, as we did not assess such ruminative thoughts following stressful events. Furthermore, when time of day was included in the analyses, the main results were unchanged, supporting that baseline negative affect directly before going to bed does not seem to be linked with next night sleep quality either. If, as argued by us and others (Babson, 2015; Fairholme & Manber, 2015), affective reactivity is the relevant phenomenon, this could also explain diverging previous results regarding negative affect predicting sleep in studies that did not include reactions to stressors (e.g., Bouwmans et al., 2017; Gerhart et al., 2017; for a review see Konjarski et al., 2018).

Participants' age did not significantly moderate the associations between affective reactivity and sleep quality. One unexpected effect indicated that after days with higher baseline negative affect than usual, participants between 60 to 67 years old reported better sleep quality. However, this age effect was no longer found when illnesses or time of day were controlled for and may thus be spurious. Because most previous studies did not differentiate between affective reactivity and baseline negative affect, these results await further replication, especially for different age groups. As older adults might have more trouble downregulating affective reactivity once it occurred (Charles & Luong, 2013) they could thus be more vulnerable to the effects of affective reactivity on sleep than younger age groups.

### **2.4.3 *Limitations***

This study examined associations among sleep quality, negative affect, stressors, and affective reactivity using data from two studies that had applied almost identical momentary

assessment designs to study the everyday lives of older adults. Design and analysis strengths include obtaining multiple assessments each day for an entire week and simultaneous consideration of how sleep quality was related to baseline negative affect and affective reactivity. There are, of course, also a number of limitations.

First, the older adults included in our study likely represent a positive selection of this age group. For example, participants of Sample 1, compared with the once representative ILSE sample, exhibited better cognitive test performance. In particular, participants in their 80s were alive, willing, and able to participate in a demanding experience sampling study. Additional research is needed to test for generalizability of results across broader and higher-risk old-age populations. Similarly, future research would benefit from including younger adults or a lifespan sample because observed effects could well differ between young adulthood, midlife, and old age.

Second, we pooled data from two studies with very similar but not completely identical assessment and sampling protocols. Sample 1 included two narrow age-groups aged 66-69 and 84-90 years, whereas Sample 2 included one group aged 61-87 years. The joint distribution was bimodal with peaks around 66-67 years and 85-86 years. While not biasing the main associations of interest, the age distribution may have limited possibility to find age moderations. Furthermore, while differences in assessment protocols (e.g., stressor occurrence items) were accommodated through inclusion of the sample variable as a predictor (with only one difference found) we cannot rule out that some differences may have seeped through.

Third, the timing of the momentary assessments, and resulting operationalization of affective reactivity, preclude the possibility to separate different stages of underlying emotion regulation processes. This could be incrementally relevant for assessing age effects, because age differences in affective reactivity/emotion regulation have been shown to depend on the time that has passed since the event (S. B. Scott et al., 2017; Wrzus et al., 2015). Details on the use of regulation strategies and ratings of regulatory success could be examined as potential moderators or explanatory variables in future research. For example, future studies might consider using event-contingent sampling (in anticipation, during, and after stressors) and/or obtaining more assessments more frequently. Similarly, it could be a promising avenue for future research to analyze physiological reactivity to stressors (e.g., by using continuous heart rate measurements) in addition to self-reports of negative affect to operationalize affective reactivity. Furthermore, emotion regulation can of course occur in different forms such as situation selection or attentional processes (Fairholme & Manber, 2015; Gross, 1998) without a stressor having previously occurred. Future work can push from the multilevel approach used in this study into idiographic approaches that (with longer time-series data) begin examining the heterogeneity of associations and possible range of underlying causes that manifest at the individual level (Nesselroade et al., 2007).



Finally, the current study used a single self-report item to measure individuals' sleep quality, which might imply limitations in two ways. First, single-item assessments may provoke concerns about reliability. However, single-item ratings of sleep quality are frequently used in sleep diaries (see Konjarski et al., 2018), and imply a significantly smaller burden on participants compared with multi-item inventories. Using multi item-inventories to assess self-reported sleep quality (e.g., Simor et al., 2015) may nonetheless increase the reliability in future studies focused on sleep quality. Second, considering relatively weak associations of sleep quality with objective measures of sleep (Kaplan et al., 2017), the validity of self-report measures of sleep quality might be questioned. It is not fully understood how individuals' perceptions of their sleep quality are linked with sleep parameters obtained from actigraphy or polysomnography. Generally, previous research including both self-reported and objective measurements of sleep quality generally found more consistent associations of subjective sleep quality versus objective measures of sleep with emotional outcomes (e.g., McCrae et al., 2008, for a review see Konjarski et al., 2018), which points to a need to distinguish perceived sleep quality from objective sleep parameters in future studies. Relatedly, because the current study focused on daily variations in self-reported sleep quality only, this could explain why our results are not fully consistent with explanations based on experimental sleep deprivation studies. Whereas experimental and laboratory studies imply limitations regarding ecological validity, objective measures of sleep quality were previously not easily obtained in naturalistic studies (Konjarski et al., 2018). With ongoing progress in technical capabilities to measure objective sleep parameters without interfering with people's natural sleep habits, future studies may benefit from additionally including objective measures of sleep along with subjective ratings of sleep quality in daily life to offer a more comprehensive description of sleep associations with negative affect in old age. However, as with multi-item inventories, using additional technology implies a significantly larger burden on participants and the scope of assessments always need to be weighed against participant burden.

#### **2.4.4 Conclusions**

Sleep quality and emotional experiences are bidirectionally linked in old age. Perhaps most important, sleep quality was found to predict baseline negative affect (in situations without previous stressors) but not affective reactivity. This may suggest that the predictive effects of sleep quality are more subtle than previously expected, at least in older adults. In contrast, only negative affective reactivity predicted next night sleep quality, suggesting that negative affect unrelated to concrete stressors may be too subtle to affect sleep quality. By including the distinction between baseline negative affect and affective reactivity, we offer a new perspective on previously inconsistent results which may have resulted from not considering the occurrence of stressors.



## CHAPTER 3

### Bidirectional Links of Daily Sleep Quality and Duration with Pain and Self-Rated Health in Older Adults' Daily Lives

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#### Abstract

**Background:** Sleep and health perceptions such as self-ratings of pain and health are closely linked. However, the temporal ordering of such associations is not well understood and it remains unclear whether sleep quality and sleep duration show similar or differential associations with health perceptions.

**Methods:** We used ecological momentary assessment data from 123 young-old (66-69 years, 47% women) and 47 old-old adults (84-90 years, 60% women). Across seven consecutive days, participants reported their sleep quality and sleep duration each morning and rated their momentary pain and health six times per day. We applied dynamic structural equation models to examine bidirectional links of morning reports of sleep quality and duration with daily levels of pain and health.

**Results:** In line with the hypotheses, results showed that when participants slept better than what is typical for them, they reported less pain and better self-rated health on the day that followed. Sleeping longer was not linked with pain or self-rated health. On days when people rated their health as better, they slept better, but not longer the following night. These associations were not moderated by age, gender, or chronic pain.

**Conclusion:** Findings suggest that in old age sleep quality is more relevant for health perceptions than sleep duration. Associations between sleep quality and self-rated health seem to be bidirectional; daily pain was linked to prior but not subsequent sleep quality.

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### 3.1 Introduction

Insufficient sleep has been linked with more intense pain and poorer self-reported health across the lifespan and particularly in old age (e.g., Edwards et al., 2008; Liu et al., 2018). Because older adults often experience changes in sleep duration and quality (Ancoli-Israel et al., 2008; Ohayon et al., 2004), as well as health declines (P. B. Baltes & Smith, 2003), their linkage is relevant for practitioners treating patients experiencing pain, general health complaints and/or sleep issues. However, whether sleep predicts subsequent health perceptions or vice versa, especially in people's everyday lives is unclear (Afolalu et al., 2018). Some studies have reported evidence for bidirectional associations between sleep and pain (Alsaadi et al., 2014; Edwards et al., 2008; O'Brien et al., 2011) while others observed only unidirectional associations (Abeler et al., 2021; Gerhart et al., 2017; Tang et al., 2012; Whibley et al., 2019). Regarding self-reported health, research has mainly studied cross-sectional associations with sleep (e.g. Liu et al., 2018; Simoes Maria et al., 2020); hence little is known about the nature and direction of daily associations. Additionally, a majority of research focuses on adults with chronic pain. To assess whether these findings generalize, the associations should be studied in a community sample as well.

#### 3.1.1 *Bidirectional Links of Sleep with Perceptions of Pain and Health*

Pain and self-rated health are two important aspects of daily physical health that have been linked with sleep (e.g., Edwards et al., 2008; Simoes Maria et al., 2020). The International Association for the Study of Pain defines pain as “an unpleasant sensory and emotional experience associated with, or resembling that associated with, actual or potential tissue damage” with the addition that “pain is always a personal experience that is influenced to varying degrees by biological, psychological, and social factors” (Raja et al., 2020, p. 1977). Self-rated health on the other hand can be defined “as an individual's overall sense of physical well-being” (Pinquart, 2001b, p. 414), so it can be considered as a broader evaluation of overall physical health. Furthermore, self-rated health is also linked with daily functioning and predicts declines in functioning and mortality above and beyond more objective measures of health (see French et al., 2012; Pinquart, 2001b). To more broadly examine the day-to-day links between sleep and physical health in older adults, we consider both pain and self-rated health.

Another important distinction is between sleep duration and sleep quality. Sleep duration is the time people spent asleep during the night, whereas sleep quality refers to a subjective evaluation of one's sleep. Sleep duration and quality are (only) moderately positively correlated (Krystal & Edinger, 2008) and have been differentially linked with physical vs. emotional outcomes. We will use daily life assessments to simultaneously study bidirectional links of sleep duration and sleep quality with pain and self-rated health in older adults' daily lives.

## *Pain*

Links between sleep and pain have been observed in cross-sectional data (J. Zhang et al., 2012). Experimental studies (Krause et al., 2019) showed that sleep deprivation decreases pain thresholds. Long-term longitudinal studies (Griffin et al., 2021) and daily diary or momentary assessment studies both observed mixed results regarding the direction of effects, with only some results supporting bidirectional associations (Abeler et al., 2021; Edwards et al., 2008; Tang et al., 2012). Thus, it remains unclear whether day-to-day associations linking sleep and pain are bidirectional.

Most research supports prospective within-person links between sleep and subsequent pain. In clinical samples, sleeping better one night predicted less intense pain the next day (Alsaadi et al., 2014; O'Brien et al., 2011) and the next morning (Gerhart et al., 2017; Raymond et al., 2001; Tang et al., 2012; Whibley et al., 2019). Lower sleep quality and sleep efficiency also predicted increased next-day pain in healthy young adults (Krause et al., 2019). No effects of sleep duration were observed in those studies that also included sleep quality as a covariate (Alsaadi et al., 2014; Krause et al., 2019; O'Brien et al., 2011; Tang et al., 2012; Whibley et al., 2019). However, in a sample of healthy older adults shorter sleep duration did predict stronger next-day pain (Edwards et al., 2008) albeit this study did not include a measure of sleep quality.

Of those studies, only some also observed a reciprocal association between pain and subsequent sleep. More intense pain during the day predicted worse next-night sleep quality in two out of five studies with clinical samples (Alsaadi et al., 2014; O'Brien et al., 2011), but not in healthy younger adults (Krause et al., 2019). Pain also predicted shorter sleep duration in healthy older adults (Edwards et al., 2008). Finally, one study only reported that pain predicted next-night sleep quality but not vice versa (Abeler et al., 2021). Overall, support may be stronger for links between sleep and subsequent pain than vice versa and more consistent for links with sleep quality than with sleep duration, at least in people living with chronic pain. Yet, this evidence is far from conclusive and warrants more research addressing bidirectional links with sleep quality and duration in a broader old age population.

Despite relatively robust links between sleep and pain, the mechanisms of these links are largely unknown (Haack et al., 2020). However, several systems linked to pain may also be influenced by sleep (e.g., opioid, melatonin, and immune systems, or the hypothalamus-pituitary-adrenal (HPA) axis). Insufficient (i.e., short or low quality) sleep seems to have a deactivating effect on pain-downregulating (i.e., analgesic) systems and an activating effect on pain-increasing (i.e., hyperalgesic) systems (Haack et al., 2020). Some of these systems (e.g., immune system and inflammatory processes, HPA axis) have also been associated with self-rated health (Christian et

al., 2011; Dahlgren et al., 2009; Nakata et al., 2010). We thus expect sleep and self-rated health to be linked similarly as sleep and pain.

### *Self-Rated Health*

In cross-sectional research, sleep and self-rated health are often associated with one another. For instance, better sleep quality is associated with better self-rated health in older adults (Burke et al., 2012; Simoes Maria et al., 2020). Also, older adults, who slept extremely short or long on average, were more likely to rate their health as poor (Liu et al., 2018; Magee et al., 2011). However, self-rated health also varies from day-to-day and week-to-week (Wolff et al., 2012).

Insufficient sleep may result in fatigue and dysregulation of endocrine and inflammatory processes which could in turn adversely impact appraisals of self-rated health (Åkerstedt et al., 2013; Christian et al., 2011). On the other hand, sufficiently long and restful sleep facilitates recovery processes (Åkerstedt et al., 2009) and thus might lead to improved appraisals of self-rated health. Supporting this, for younger adults, self-rated health continually decreased during a five-night sleep restriction protocol and increased back to initial levels after three nights of recovery sleep; this effect was (partially) mediated by fatigue (Lekander et al., 2013). Similar associations have been observed in daily life, increased sleepiness during the day (which was predicted by both sleep quality and sleep duration) predicted worse reports of self-rated health in a lifespan sample (Åkerstedt et al., 2013).

Regarding potential predictive effects of self-rated health for subsequent sleep, people with better self-rated health not only reported better overall sleep quality, but also shorter times to fall asleep (Simoes Maria et al., 2020). Transferring this to daily associations, when people feel more comfortable and have fewer physical symptoms of illness, they could also experience better or longer sleep. Overall, we thus expect daily associations between sleep and self-rated health similar to those expected for pain.

### **3.1.2 Age, Sex, Chronic Pain, and Time-of-day as Covariates**

Participant's *age* is one important factor to consider when studying links of sleep with pain and self-rated health. Old-old, as compared with young-old, age is associated with increased vulnerabilities and functional decline (P. B. Baltes & Smith, 2003), which could be a risk factor for closer links of insufficient sleep with pain and self-rated health. However, in a cross-sectional analysis, the association of back pain with sleep problems was stronger for adults in late middle age (50-59 years old) than for adults in late old age (older than 80 years; Chaudhary & Selvamani, 2021). Also, links between objective physical health and self-rated health are weaker with older ages (P. B. Baltes & Smith, 2003), but links with sleep have not been studied. Accordingly, old-old adults' sleep could also be less closely linked with their pain or self-rated health. Overall, young-old and old-old

adults may differ in daily associations between sleep and pain as well as self-rated health, but the exact nature of such differences remains unclear.

Sex differences may also exist. For example, in one study middle-aged women and men without insomnia experienced similar levels of pain, whereas women with insomnia experienced more pain (J. Zhang et al., 2012). On the contrary, a link between sleep duration and self-rated health was only observed among Korean older men but not women (Hwang & Kim, 2020).

So far, links between sleep and pain have most often been assessed for people living with *chronic pain*, however, differences in cognitive and emotional processes relating to chronic pain, could also entail different links between sleep and pain in the general population of older adults (Abeler et al., 2021; Irwin et al., 2012; Ramlee et al., 2018). The presence of chronic pain should thus be considered when studying links between sleep and pain.

Finally, links between sleep and perceptions of physical health may also differ depending on the *time of day*. For example, better sleep quality predicted less pain in the morning but often not later during the day (Gerhart et al., 2017; Tang et al., 2012). Similarly, in one study only nightly pain but not pain during the day was associated with that night's sleep quality and sleep duration (Raymond et al., 2001). No research has yet examined time-related differences for self-reported health.

### **3.1.3 Current Research**

In this paper, we examine bidirectional links of sleep quality and sleep duration with pain and self-rated health in daily life using momentary assessment data from 170 older adults. First, we expected that worse sleep quality is linked with experiencing more pain (H1a) and worse self-rated health the following day (H1b). Similarly, we predicted that shorter sleep duration is also linked with experiencing more pain (2a) and worse self-rated health the following day (2b). Furthermore, we expected that experiencing more intense pain or worse self-rated health than usual is linked with worse sleep quality (H3a/3b) as well as shorter sleep duration the following night (H4a/4b). Testing these hypotheses, we considered age (young-old versus old-old), sex, and chronic pain as moderators on the associations. We also considered differential links of sleep with pain and self-rated health assessments in the morning and evening.

## **3.2 Methods**

### **3.2.1 Sample**

Participants in the current study (EMIL) were mainly recruited from the long term-longitudinal interdisciplinary study of adulthood ILSE (Sattler et al., 2017). The main predictor for taking part in the current study was cognitive performance at the last wave of ILSE (2014-2017;

Schilling et al., 2022). Data were collected in 2018 and 2019 in Heidelberg and Leipzig, Germany. The sample includes data from 123 young-old (66-69 years old, 47% women) and 47 old-old adults (85-90 years old, 60% women) who participated in the momentary assessment phase of the larger EMIL study (for more details see <https://osf.io/fczmg/>). Of the old-old adults 15 participants, who were not part of the original ILSE sample, were additionally recruited from the community. Most participants were married (62.4%,  $n = 106$ ). The remaining participants were widowed (17.6%,  $n = 30$ ), divorced (13.5%,  $n = 23$ ), or single (5.3%,  $n = 9$ ). One person did not report their family status. On average, participants completed 14.5 years of formal education ( $SD = 2.5$ ).

### 3.2.2 Procedure

The project was approved by the ethics committees of the University of Heidelberg and the German Society for Psychology (DGPs) and participants provided written informed consent. Participants answered the momentary assessments on identical study touch-screen tablets (Apple iPad) they had received during the instruction session. Five participants used paper-pencil versions of the questionnaires instead because they were uncomfortable using the iPad. Participants had access to continuous phone support and a scheduled phone call on the second assessment day to clarify questions. Every day of the seven-day assessment period, participants answered up to six brief questionnaires on the iPad: the first questionnaire was completed right after waking (i.e., self-initiated), with the following assessments scheduled and prompted to be answered at 10am, 1pm, 4pm, 7pm, and 9pm. To accommodate daily schedules, there was a leeway of 30 minutes before and two hours after the prompted times.

At the first assessment each morning, participants reported on their momentary levels of pain, rated their health, and then answered questions about their previous night's sleep. At all other assessments, participants reported on their momentary pain and health. The assessments also included questions on momentary affect, stress experiences, and emotion regulation that are not relevant to the current study (for details on the complete assessment see <https://osf.io/fczmg/>). Adherence to the assessment protocol was very high: Participants provided data on 6.9 ( $SD = 0.8$ ) of the 7 days and responded to 5.8 ( $SD = 0.5$ ) of the 6 assessments per day. Overall, we used data from 1,165 days provided by 170 participants in this study.

### 3.2.3 Measures

#### *Sleep Quality and Duration*

In the first morning assessment after waking up, participants answered questions about their sleep in the previous night. They rated their sleep quality ("How was the overall quality of your sleep?") using a slider from 0 = *extremely bad* to 100 = *extremely good* (for similar assessments



of sleep quality see, e.g., Gerhart et al., 2017; Tang et al., 2012). In addition, they reported their total sleep duration (“How many hours did you actually sleep?”) in hours and minutes.

#### *Momentary Pain*

At each momentary assessment (i.e., up to six times per day), participants reported their current pain intensity (“How much pain or physical discomfort are you experiencing right now?”) using a slider from 0 = *none at all* to 100 = *extreme*. For the main analyses, the daily ratings were averaged to form one daily measure of pain.

#### *Momentary Self-Rated Health*

At each momentary assessment (i.e., up to six times per day), participants reported a current rating of their health (“How would you rate your state of health at the moment?”) using a slider from 0 = *very bad* to 100 = *excellent*. For the main analyses, the daily ratings were averaged to form one daily measure of self-rated health.

#### *Chronic Pain and Medical Conditions*

Amongst other questionnaires (for details see <https://osf.io/fczmg>), participants answered questions regarding their general physical health and the presence of 36 medical conditions (Knoll et al., 2020a). Because we did not assess chronic pain specifically, the 36 medical conditions were rated by a general practitioner regarding whether they are typically associated with chronic pain, identifying osteoarthritis/arthritis, dorsalgia, osteoporosis, rheuma/fibromyalgia, moderate to severe liver disease, and metastases. In the following, these medical conditions will be referred to as chronic pain related medical conditions. If participants endorsed one of these conditions, they were asked how much it burdened them (1 = *not at all*, 4 = *extremely*). Participants who reported to be burdened at least somewhat by any of those conditions were considered as likely experiencing chronic pain (*yes* = 1, *no* = 0). In this sample, 42.5% of participants reported osteoarthritis/arthritis, 52.7% dorsalgia, 12.4% osteoporosis, 8.6% rheuma/fibromyalgia, 1.1% moderate to severe liver disease, and 1.6% metastases.

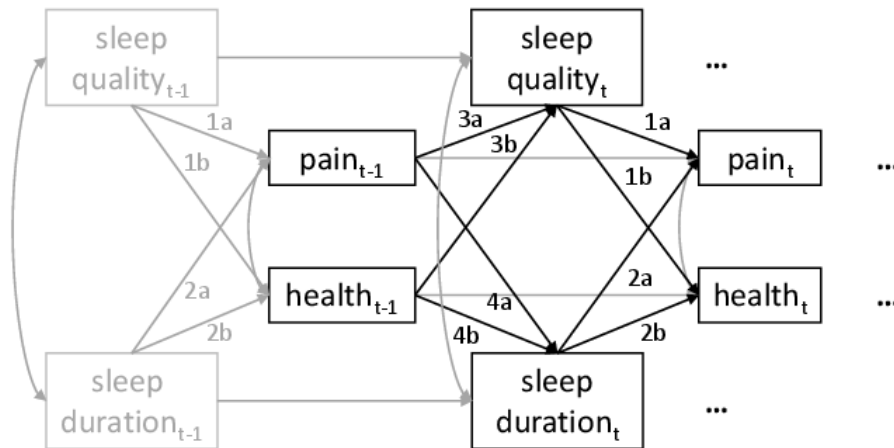
### **3.2.4 Analytic Strategy**

To test the bidirectional hypotheses concurrently while accounting for the nested data, we applied twolevel dynamic structural equation modeling (DSEM; McNeish & Hamaker, 2019) using the Bayes estimator in Mplus (Version 8.4; L. K. Muthén & Muthén, 1998-2017). We averaged pain and self-rated health ratings across each day and included the daily averages in the main model. Daily pain and self-rated health were predicted by the previous night’s sleep quality and sleep duration. Conversely, sleep duration and quality were predicted by the previous day’s pain and self-rated health (see Figure 3.1 for a graphical illustration of the model). Furthermore, autoregressive paths linked current and previous day’s pain and health as well as current and previous night’s

sleep. All these within-person associations were implemented as random slopes that could vary between persons. The person-means (of pain, self-rated health, sleep quality, and sleep duration) were modelled as latent between-person variables on Level 2. For more details on the analytic strategy and estimation see Supplement S1.

**Figure 3.1**

Structure of the Within-Person Part (Level 1) of the Dynamic Structural Equation Model.



*Note.* All paths are implemented as random slopes and all variables included a random intercept varying between-persons. Pain = daily average of momentary pain. Health = daily average of self-rated health.

### Additional Analyses

In additional analyses, we tested the effects of potential moderators on the bidirectional links: Age group, sex, and the presence of medical conditions linked with chronic pain. These moderators were entered as Level 2 predictors of the latent person-means of pain, self-rated health, sleep quality, and sleep duration, as well as the bidirectional random slopes. All moderators were centered on their grand-mean.

To provide a comprehensive picture of associations with and without controlling for related parameters, we additionally specified four models addressing bidirectional links between each of the health indicators and each of the sleep characteristics separately (i.e., pain – sleep quality, pain – sleep duration, self-rated health – sleep quality, self-rated health – sleep duration).

Furthermore, we conducted an analysis in which pain and self-rated health were not averaged across the day but instead we used the first morning measurement (after waking) to be predicted by the previous night's sleep and the last evening assessment (ca. 9pm) to predict next-night sleep. The model is illustrated in the supplement (Figure S2).

### **3.2.5 *Transparency and Openness***

We provide documentation on all measures assessed in the study and analysis scripts for main and additional analyses at <https://osf.io/fczmg/>. Because this was a rather small longitudinal study we are not in a position to make data publicly available because the data contain information that could compromise research participants' consent and privacy (e.g., health information). The data presented in this study are however available in a moderated fashion from the ILSE team. Towards that end, we have established procedures in the ILSE study over the past ten and more years that we have successfully implemented numerous times. Data will thus be made available upon request to the authors.

**Table 3.1**

Descriptive Statistics and Within-Person (below the central diagonal) and Between-Person (above the central diagonal) Correlations Between the Variables of Interest.

	M	SD	Average iSD	ICC	Pain	SRH	Sleep Quality	Sleep duration	Cohort	Sex	Chronic pain
Pain <sup>a</sup>	20.81	23.26	6.37	0.88	-	<b>-0.72</b>	<b>-0.30</b>	-0.13	<b>0.43</b>	<b>-0.21</b>	<b>0.38</b>
Self-rated health <sup>a</sup>	71.47	21.07	4.68	0.87	<b>-0.31</b>	-	<b>0.42</b>	<b>0.17</b>	<b>-0.34</b>	0.13	<b>-0.42</b>
Sleep quality <sup>a</sup>	68.16	23.09	9.18	0.38	<b>-0.10</b>	<b>0.12</b>	-	<b>0.36</b>	-0.07	0.12	<b>-0.18</b>
Sleep duration	6.72	1.33	0.44	0.53	<b>-0.06</b>	<b>0.09</b>	<b>0.38</b>	-	-0.04	0.02	-0.15
Cohort (old-old) <sup>b</sup>	27%	-	-	-	-	-	-	-	-	-0.11	<b>0.16</b>
Sex (male) <sup>c</sup>	50%	-	-	-	-	-	-	-	-	-	-0.13
Chronic pain <sup>d</sup>	70%	-	-	-	-	-	-	-	-	-	-

Note. iSD = intra-individual standard deviation. ICC = intra-class correlation coefficient.

<sup>a</sup> Scale 0–100. <sup>b</sup> 0 = young-old adults, 1 = old-old adults. <sup>c</sup> 0 = female, 1 = male. <sup>d</sup> 0 = did not endorse any chronic pain related medical conditions.

1 = endorsed at least one chronic pain related medical condition.

**Bold faced** estimates indicate  $p < .05$

### 3.3 Results

We report descriptive statistics and correlations between the relevant variables in Table 3.1. Overall, participants reported relatively low levels of pain and relatively high levels of self-rated health, and sleep quality. On average, they slept about 6.72 hours per night.

Zero-order correlations on the within-person level showed that on days when people slept better or longer than usual they reported less pain and better self-rated health. On the between-person level, people who slept better on average also reported less average pain and better self-rated health, and people who slept longer reported better self-rated health (Table 3.1).

#### 3.3.1 *Bidirectional Links of Sleep Quality and Sleep Duration with Pain and Self-Rated Health*

Model results (Table 3.2) showed that when people reported better sleep quality than usual, they also reported lower pain and better self-rated health the following day, supporting hypotheses H1a and H1b. In contrast and contradicting H2a or H2b, sleeping longer than usual was not linked with pain or self-rated health the following day. These results are illustrated in Figure 3.2 (Panels A and B).

In the same model, we analyzed links of pain and self-rated health with subsequent sleep quality and duration. How much pain people experienced during the day, was not significantly linked to sleep quality the following night, not supporting H3a. However, in line with H3b, when they experienced worse self-rated health, they reported worse sleep quality the following night. Neither experiencing pain nor self-rated health was linked with subsequent sleep durations, thus not supporting Hypotheses H4a and H4b. These results are illustrated in Figure 3.2 (Panels C and D).

The autoregressive coefficients indicated some stability of pain and self-rated health. When people experienced increased or decreased pain or poor self-rated health one day, their pain and self-rated health the next day tended to shift back towards their person-mean. In contrast, the low and insignificant autoregressive coefficients of sleep quality and sleep duration indicate that the intraindividual day-to-day changes in both sleep indicators unstably fluctuate around the respective person-means. Furthermore, pain and self-rated health were correlated within and between persons, that is, days with increased pain were also characterized by decreased self-rated health, and people who experienced stronger pain on average also reported worse self-rated health on average. Similarly, following nights when people slept longer, they also reported having slept better (within-person) and on average, people who slept longer also slept better (between-person). Finally, people who experienced stronger pain and worse self-rated health on average, also reported lower average sleep quality and shorter average sleep durations (between-person).

**Table 3.2**

Results from the Dynamic Structural Equation Model Analyzing Bidirectional Associations Between Sleep Quality, Sleep Duration, Pain, and Self-Rated Health.

	Path/ Hypothesis	Estimate	95% Credible Interval		Standardized Estimate
			lower	upper	
<b>Within Person</b>					
Pain on sleep quality	1a	<b>-0.043</b>	-0.078	-0.008	-0.078
Pain on sleep duration	2a	-0.127	-0.869	0.656	-0.015
Health on sleep quality	1b	<b>0.050</b>	0.015	0.085	0.089
Health on sleep duration	2b	0.588	-0.145	1.298	0.059
Sleep quality on pain	3a	-0.068	-0.213	0.081	-0.041
Sleep quality on health	3b	<b>0.202</b>	0.048	0.352	0.115
Sleep duration on pain	4a	-0.003	-0.014	0.008	-0.030
Sleep duration on health	4b	0.000	-0.010	0.010	0.004
Pain AR1		<b>0.599</b>	0.502	0.689	0.559
Health AR1		<b>0.590</b>	0.503	0.674	0.558
Sleep quality AR1		0.076	-0.026	0.184	0.080
Sleep Duration AR1		0.024	-0.055	0.119	0.030
Pain with health		<b>-17.230</b>	-21.777	-13.086	-0.333
Sleep quality with duration		<b>5.902</b>	4.759	7.150	0.389
<b>Between Person</b>					
Pain intercept		<b>21.601</b>	17.706	25.502	
Health intercept		<b>73.503</b>	70.299	76.678	
Sleep quality intercept		<b>67.988</b>	65.272	70.701	
Sleep duration intercept		<b>6.775</b>	6.612	6.934	
Pain with health		<b>-355.790</b>	-473.000	-268.867	
Pain with sleep quality		<b>-115.162</b>	-194.590	-48.833	
Pain with sleep duration		<b>-5.097</b>	-9.672	-0.853	
Health with sleep quality		<b>122.310</b>	66.457	191.878	
Health with sleep duration		<b>4.416</b>	0.780	8.377	
Sleep quality with duration		<b>4.831</b>	1.959	8.204	
<b>(Residual) Variances</b>					
<b>Within-Person</b>					
Pain		54.403	48.010	61.604	
Health		49.295	43.897	55.483	
Sleep quality		299.350	269.717	332.323	
Sleep duration		0.782	0.706	0.869	
<b>Between Person</b>					
Pain		479.549	364.491	634.869	
Health		299.092	219.466	405.254	
Sleep quality		175.327	119.674	249.337	
Sleep duration		0.661	0.427	0.966	
Pain on sleep quality		0.004	0.001	0.013	
Pain on sleep duration		3.564	0.560	9.452	
Health on sleep quality		0.007	0.002	0.018	
Health on sleep duration		3.072	0.703	7.723	
Sleep quality on pain		0.068	0.009	0.223	

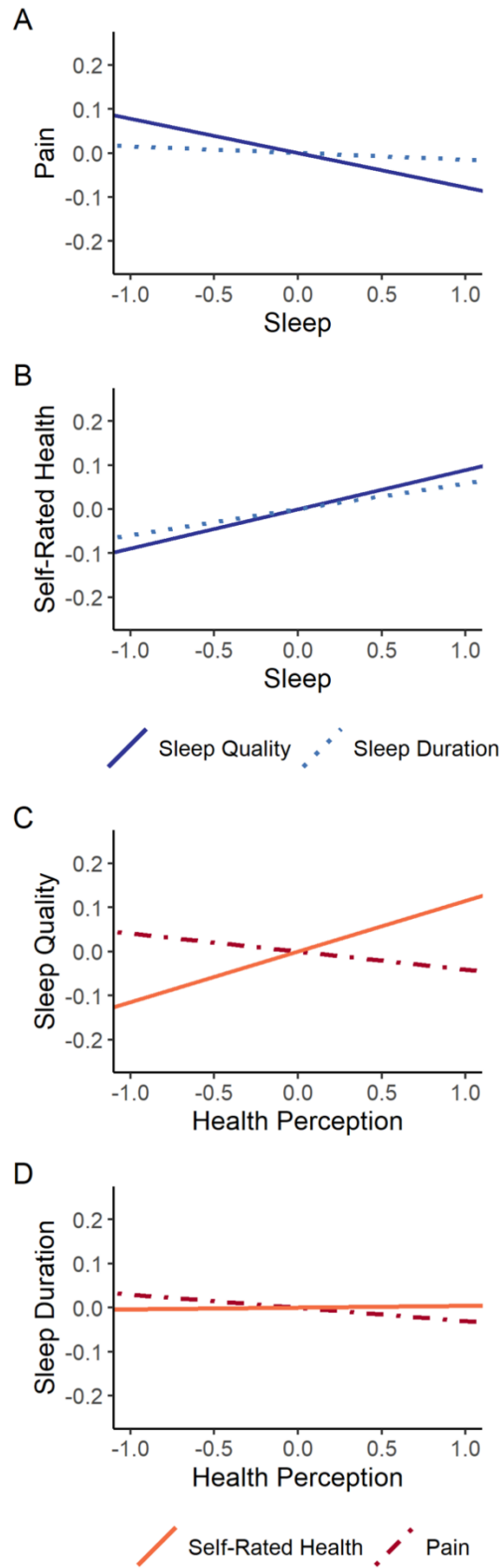
Path/ Hypothesis	Estimate	95% Credible Interval		Standardized Estimate
		lower	upper	
Sleep quality on health	0.095	0.020	0.240	
Sleep duration on pain	0.001	0.001	0.002	
Sleep duration on health	0.001	0.001	0.001	
Pain AR1	0.111	0.077	0.158	
Health AR1	0.088	0.058	0.131	
Sleep quality AR1	0.090	0.044	0.153	
Sleep Duration AR1	0.025	0.003	0.074	
<b>Model-Explained Variance</b>				
R <sup>2</sup> Pain	<b>0.458</b>	0.259	0.525	
R <sup>2</sup> Health	<b>0.486</b>	0.423	0.542	
R <sup>2</sup> Sleep quality	<b>0.201</b>	0.145	0.253	
R <sup>2</sup> Sleep duration	<b>0.255</b>	0.190	0.312	

*Note.* The paths/hypotheses are illustrated in Figure 1. Pain = daily average of momentary pain. Health = daily average of self-rated health. Standardized estimates refer to within-person standardized estimates averaged over clusters which can be used to compare the size of effects (Schuurman et al., 2016). AR1 = Autoregression with lag 1.

**Bold faced** estimates indicate that the 95% CI does not cover 0

**Figure 3.2**

Standardized Regression Coefficients of Sleep Predicting Subsequent Health Perceptions (A and B) and Health Perceptions Predicting Subsequent Sleep (C and D).





### 3.3.2 Additional Analyses

We considered participants age group, chronic pain, and sex as potential moderators of the links of pain and self-rated health with sleep quality and sleep duration (see Supplementary Table S3). First regarding main effects of the covariates, being an old-old adult (compared with a young-old adult), a woman (vs. a man), and having chronic pain related medical conditions, were all linked with experiencing stronger pain on average. Being an old-old adult or having chronic pain related medical conditions was also linked with worse self-rated health. None of these characteristics were associated with sleep quality, but having a chronic pain related medical condition was associated with a shorter average sleep duration.

Second, age group, sex, and chronic pain generally did not moderate the links between pain, self-rated health and sleep. Only one significant effect of sex on the link between self-rated health and subsequent sleep duration occurred. This link was significantly stronger for women than for men, albeit not in itself significant for either sex (women:  $b = 0.012$ , 95% CI [-0.003, 0.027]; men:  $b = -0.012$ , 95% CI [-0.025, 0.002]).

When bivariate associations between each of the health perceptions and each of the sleep characteristics were considered in four separate models, the main results were replicated and some additional associations emerged: Shorter sleep duration predicted worse next-day self-rated health ( $b = 1.078$ , 95% CI [0.434, 1.731]) and increased pain predicted worse next-night sleep quality ( $b = -0.157$ , 95% CI [-0.291, -0.032]). Neither of these effects was statistically significant in the main model. Full results for these models are reported in the Supplement (Table S4).

Considering only morning and evening assessments, sleep quality predicted both pain and self-rated health in the morning; the respective unstandardized estimates, as well as the standardized coefficients predicting the morning assessments were numerically larger than those listed for the daily averages in Table 2. In contrast to the main model, self-rated health around 9pm (vs. across the day) did not significantly predict sleep quality the following night. No other differences emerged. For full results see Table S5 in the Supplement.

### 3.4 Discussion

In this study, we assessed bidirectional links between health perceptions and sleep in a sample of older adults. Briefly summarized, the results showed that when people slept better than usual one night, they reported reduced pain and better self-rated health, but this was not true when they merely slept longer than usual. This is noteworthy, as sleeping longer is usually accompanied by sleeping better (Krystal & Edinger, 2008). Regarding the opposite direction, only experiencing better than usual self-rated health predicted better next-night sleep quality. This pattern of findings revealed partial support for the hypotheses, which may add to a more fine-grained picture of the

interplay between nightly sleep and daily health perceptions in old and very old age which we discuss in the following.

#### **3.4.1 Sleep Quality, but not Duration, Predicts Next-Day Health Perceptions**

Regarding the links between sleep and next-day pain and self-rated health, the results only partially supported the hypotheses. Contrary to our expectations, sleeping shorter than usual predicted neither increased pain, nor poorer self-rated health across the next day. However, this finding aligns with previous research which mostly observed that sleep quality but not duration predicted increased pain when both were included in the same prediction model (e.g., Alsaadi et al., 2014; O'Brien et al., 2011). Naturalistic daily links between sleep and self-rated health had not previously been studied, but as predicted and expected from cross-sectional research (e.g., Simoes Maria et al., 2020), our research showed that intraindividual day-to-day variations in sleep quality were linked with next-day self-rated health. However, cross-sectional associations between sleep duration and self-rated health (e.g., Magee et al., 2011) did not generalize to within-person links when both sleep quality and duration were simultaneously considered as predictors. Notably, when sleep duration was considered in a separate model, longer sleep duration did predict better self-rated health the following day. Altogether, these findings suggest a more important role of people's sleep quality than their sleep duration for daily perceptions of pain and health. Taking into account the observed within-person covariation between daily sleep duration and quality, the predictive effects of sleep duration unadjusted for sleep quality may reflect the relevance of sleep quality, rather than unique effects of duration.

The weak predictive effects of sleep duration stand in notable contrast to findings from experimental studies. As previously mentioned, severely or completely restricted sleep duration indeed affected subsequent health outcomes (Krause et al., 2019; Lekander et al., 2013). In the data analyzed for the current study, sleep duration was generally within relatively normal ranges (Ohayon, 2004) and sleep duration showed less within-person variance than sleep quality (as revealed by the ICCs in Table 1). Therefore, sleep duration could matter when it comes to more extreme curtailments of sleep time.

#### **3.4.2 The Relevance of Self-Rated Health, but not Pain, for Sleep**

Regarding links of pain and self-rated health during the day with subsequent sleep, the hypotheses were again only partially supported. Only self-rated health, but not daily pain, predicted sleep quality, whereas neither predicted sleep duration. Thus, it was again sleep quality, but not sleep duration, which was linked with daily health perceptions. Pain additionally predicted sleep quality in the separate bivariate model when self-rated health was not controlled for. Considering

the substantial within-person correlation between pain and self-rated health, this may indicate that only shared aspects of pain that feed into more general physical health perceptions, as captured by self-rated health, are linked with subsequent sleep quality. It thus may be concluded that people's feeling more or less healthy across days operates as a key predictor for how well they sleep at night. Deviations from one's individual level of self-rated health may be perceived as alarming (or reassuring), for instance potentially causing health worries and rumination which could carry over into nighttime. One might think that this is particularly true for older adults who are more threatened by potential health loss than people at younger ages.

Surprisingly, however, whereas self-rated health averaged across the day did predict worse sleep quality the following night, this was not the case for self-rated health around 9pm. This may speak against carry over effects of rumination or health worries explaining links between self-rated health and subsequent sleep quality. Rather, processes associated with these health perceptions that unfold across the day might be the relevant mediator. For example, self-rated health has been associated with dysregulated HPA axis activity (Dahlgren et al., 2009) and increased inflammation (Christian et al., 2011) so one could speculate about more systemic rather than momentary influences. An alternative explanation is that average daily self-rated health captures cumulative effects: If people have been feeling unwell the whole day versus only in the late evening, this might represent a stronger burden that could carry over into sleep.

We were surprised that pain experienced across the day did not predict nighttime sleep quality (by contrast to self-rated health), although this result partially aligns with previous findings where only some studies found pain to be predictive of sleep quality (e.g., Alsaadi et al., 2014; O'Brien et al., 2011; but see Krause et al., 2019; Tang et al., 2012). Next, we discuss some speculative explanations for this finding.

First, across the sample, pain was relatively low on average and rather stable intraindividually – this may suggest that smaller daily variations in pain are not that important for next-night sleep. However, self-rated health varied similarly and still predicted sleep quality. Our findings, though, do not rule out that more extreme experiences of daily pain could interfere with nighttime sleep quality.

Second, pain may matter for sleep to the degree that it persists into the night. For instance, in a study of patients being treated in the hospital for burn-injuries, pain throughout the day did not predict sleep quality in the following night, but when the patients experienced increased pain during the night itself, they did sleep worse (Raymond et al., 2001). In the current study, we only obtained ratings of pain during the day. However, approximating night-time ratings with the last assessment before participants went to bed, this assessment around 9 pm was not linked with the following night's sleep quality or duration either.

Third, it is possible that links of pain and self-rated health with subsequent sleep may partially depend on other variables, for example attention to pain (Affleck et al., 1996), depressive symptoms (O'Brien et al., 2011), or affective reactivity to pain (Frumkin & Rodebaugh, 2021; Hamilton et al., 2007). As we have previously shown (Lücke et al., in press) stronger affective reactivity to stressors but not baseline negative affect was linked with decreased subsequent sleep quality and it seems possible, that this could also be true for affective reactivity to health perceptions such as pain or self-rated health.

### **3.4.3 *The Role of Age, Sex, and Chronic Pain***

We considered participant's age group, sex, and chronic pain as potential moderators. We did not observe any differences assessed in links between sleep and pain or self-rated health between people with vs. without chronic pain related medical conditions. While people with chronic pain related medical conditions did in fact experience more intense pain and worse self-rated health overall, we still refrain from further interpreting these results as the measure we used was devised ad-hoc and might not identify every participant with or without chronic pain reliably. Neither sex nor age significantly modified links between sleep and pain either. Sex modified the link between self-rated health and sleep duration but this effect was not significant for either sex.

While we did not observe significant moderating effects of age group, sex, or chronic pain, with interventions in mind, further research should investigate other potential moderators of within-person links. Results from an interdisciplinary intervention program for chronic pain showed that longer-term changes in sleep duration were only linked with longer-term changes in pain for people with stronger daily links between sleep duration and pain (Davin et al., 2014). It thus seems worthy to identify whose sleep is linked with their pain and self-rated health and for whom it could thus be helpful to simultaneously target sleep and pain in interventions.

### **3.4.4 *Limitations***

Three sets of limitations have to be considered when interpreting the results of the current study. First, with relatively good health, the participants in this study likely represent a positive selection from the population of older adults and more research is required to assess whether our results generalize to more vulnerable groups. Second and partially resulting from this positive selectivity, the variance in some variables may be restricted: Many participants in this study experienced relatively little pain, reported good health, and varied relatively little therein across the study. Similarly, on average, sleep duration varied less than half an hour from night to night. This implies that some associations may have been underestimated because of restricted variance,

also putting the small observed effects into perspective. Nonetheless, small effects are normal and expected in daily life and can still have important long-term consequences.

Third, limitations also stem from the measures used. This study relied on self-reported sleep quality and duration which are not in complete concordance with actigraphy or polysomnography. Despite more consistent links with self-reported compared with otherwise measured sleep in previous research (e.g., Abeler et al., 2021; O'Brien et al., 2011), additionally actigraphically measuring sleep in daily life may complete the picture. Furthermore, more detailed assessments of pain in daily life and a more appropriate measure of chronic pain would be desirable for future studies (see, e.g., Fillingim et al., 2016; Schiavenato & Craig, 2010; Stone et al., 2021). Future research may consider explicitly recruiting participants with and without chronic pain to be able to assess differences between those groups more distinctly.

### **3.4.5 Conclusion**

In older adults' daily lives, sleep quality seems more important in predicting daily health perceptions than sleep duration. Links of sleep quality with self-rated health are likely bidirectional; better sleep quality went along with better next-day self-rated health which again went along with better sleep quality the following night. In contrast, sleep quality was associated with next-day pain but not vice versa. The results suggest that sleep interventions could potentially be useful to improve older adults' health perceptions.



## CHAPTER 4

### Between-Person and Within-Person Associations of Sleep and Working-Memory in the Everyday Lives of Old and Very Old Adults: Initial Level, Learning, and Variability

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#### Abstract

**Study Objectives:** Sleep duration affects various aspects of cognitive performance, such as working-memory and learning, among children and adults. However, it remains open, whether similar or even stronger associations exist in old and very old age when changes in sleep and cognitive decrements are common.

**Methods:** Using repeated daily-life assessments from a sample of 121 young-old (66-69 years old) and 39 old-old adults (84-90 years old), we assessed links between sleep duration and different aspects of working-memory (initial level, practice-related learning, and residualized variability) between and within persons. Participants reported their sleep durations every morning and performed a numerical working-memory updating task six times a day for seven consecutive days.

**Results:** Both people who slept longer and those who slept shorter than the sample average showed lower initial performance levels, but a stronger increase of WM over time (i.e., larger learning effects), relative to people with average sleep. Sleep duration did not predict performance variability. Within-person associations were found for people sleeping relatively little on average: For them, working-memory performance was lower on days with shorter than average sleep, yet higher on days with longer than average sleep. Except for lower initial levels of working-memory in old-old adults, no differences between young-old and old-old adults were observed.

**Conclusion:** We conclude that sufficient sleep remains important for working-memory performance in older adults and that it is relevant to include different aspects of working-memory performance, because effects differed for initial performance and learning.

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## 4.1 Introduction

Sleep affects many aspects of human daily life, for example mood (Konjarski et al., 2018), social relationships (Gordon et al., 2021), and cognition (Lowe et al., 2017). Adults who sleep within a normal range (7-8 hours) show higher cognitive performance than those who generally sleep considerably less or more (Lo et al., 2016) – yet sleep duration also differs within persons from one night to the next.

Furthermore, sleep affects learning – participants who slept after learning improved on cognitive tasks compared to participants who stayed awake (Kuriyama et al., 2008; Zinke et al., 2018) and improvements were impeded among participants whose sleep was restricted over extended periods of time (van Dongen et al., 2003). Lastly, sleep deprivation has been associated with performance inconsistencies, that is, increased variability in cognitive performance (Doran et al., 2001).

Although most of these previous studies took place under controlled lab conditions, first results also point to associations between sleep duration and cognitive performance (specifically working-memory) in daily life (Könen et al., 2015). Still, it is largely an open question how daily variations in sleep duration affect different aspects of cognitive performance such as learning and performance variability in daily life. Notably, in contrast to findings on sleep duration, variation in sleep quality was generally not associated with cognitive performance in young adulthood or old age (Gamaldo et al., 2010; Holanda & Almondes, 2016; Zavec et al., 2020) which is why we focus on sleep duration in this report.

Examining daily variations in sleep and cognitive performance in old and very old age is particularly relevant for at least two reasons: First, older adults often experience changes in their sleep (Garbarino et al., 2021; J. Li et al., 2018; Ohayon et al., 2004) and reductions in cognitive abilities (Finkel et al., 2003). Second, short (i.e., insufficient) sleep may increase older adults' risk for cognitive decline and the incidence of dementia as well as negatively influence the progression thereof (Scullin & Bliwise, 2015; Wennberg et al., 2017). So far, studies on associations between everyday sleep durations and cognitive performance in old age have produced mixed results (Devore et al., 2016; Lo et al., 2016; Scullin & Bliwise, 2015). Importantly, previous research has mainly studied influences of sleep on mean cognitive performance, but we know little about learning or performance variability. Learning and variability are important aspects of cognitive performance in their own right (e.g., because these predict later health outcomes such as mortality, Batterham et al., 2014; see also Allaire & Marsiske, 2005; Lövdén et al., 2007; L. Yang et al., 2006) that can only be assessed given a sufficient number of measurements. Advantages of repeatedly assessing performance in daily life include, in particular, higher measurement accuracy and



increased ecological validity compared with one-off lab assessments (Daniëls et al., 2020).

Overall, there is a need to better understand links between sleep duration with distinct aspects of daily cognitive performance in old age, which both vary from day to day. This is certainly interesting for researchers from different fields, including sleep as well as aging research. In addition, clinicians providing care to older patients might benefit from this knowledge. For example, when sleep problems reduce cognitive performance (Lo et al., 2016; Sternberg et al., 2013), this temporarily lowered cognitive performance in addition to increased subjective cognitive complaints (Tardy et al., 2015) may lead to patients being misdiagnosed as cognitively impaired (Edmonds et al., 2014) when dealing with potential sleep problems instead could attenuate cognitive issues as well (Bademli et al., 2019). In this study, we focus on working-memory (WM) which is an important factor for general cognitive functioning in old age (Verhaeghen, 2018). We thus aim to extend past research by addressing how self-reported daily sleep duration across one week is linked with the level of WM performance, as well as practice-related improvements in a WM task across time, and variability in WM performance in two late life age groups as participants went about the routines of their everyday lives. Furthermore, we examine how daily (within-person) variations in sleep duration are associated with daily levels of WM performance.

#### **4.1.1 Sleep Duration and WM Performance**

WM is central to the concurrent holding and processing of relevant information (Baddeley, 1992). As part of the executive control functions (updating), it is considered the basis for higher cognitive operations such as reasoning or language comprehension (Baddeley, 1992; Diamond, 2013). Higher WM capacity has thus been found to be associated with better general cognitive functioning (Conway et al., 2003). Keeping information in mind and updating this information is also crucial in everyday life, for example, in pursuing goal-oriented behavior (Hofmann et al., 2008). WM capacity has a stable and trait-like component, but it also varies intra-individually (Dirk & Schmiedek, 2016; Ilkowska & Engle, 2010), for example along with variations in affect, motivation, or sleep duration (Brose et al., 2012; Könen et al., 2015; Riediger et al., 2011). Furthermore, WM performance can improve with practice, although the long-term benefits and breadth of transfer of such training are debated (Richmond et al., 2011; Sala et al., 2019; Shipstead et al., 2012; Zinke et al., 2014). Thus, WM performance varies within and between persons and sleep seems to be a relevant factor to predict such variations at both levels (Gamaldo et al., 2010; Könen et al., 2015; Sternberg et al., 2013).

Considering neuroscientific explanations, insufficient sleep, both on certain days and in general, is thought to impair cognitive function through reducing vigilance, attention, and frontal-lobe function (Lim & Dinges, 2010). Reduced activation in frontal brain networks in particular

could explain impairments in specific higher cognitive functions involving the prefrontal cortex such as WM (Frenda & Fenn, 2016). Thus, two distinct processes may be involved: First, at the within-person level, insufficient sleep could directly result in lower WM performance the next day (i.e., acute sleep loss, short-term effects). Second, at the between-person difference level, people who generally get insufficient sleep could show lower WM performance compared to people with generally sufficient sleep (i.e., chronic sleep loss, possible long-term effects).

Such conceptual considerations align well with past empirical results: WM performance is impaired after total sleep deprivation, and also after sleep restrictions (Casement et al., 2006; Lowe et al., 2017; van Dongen et al., 2003), which is more similar to experiences people have in their daily lives. A recent meta-analysis showed short-term effects of sleep restriction compromising executive control functions in general, and WM specifically, in studies ranging from one to a few days (Lowe et al., 2017). Importantly, studies have also reported non-linear associations of average sleep duration with cognitive performance, including WM specifically: Both people with overly long and very short habitual sleep duration showed lower cognitive and WM performance (Lo et al., 2016; Sternberg et al., 2013). Associations of longer sleep duration with lower cognitive performance are interpreted as reflecting common links with weakened circadian rhythms, inflammatory processes, or physical or mental comorbidities (Devore et al., 2016; Lo et al., 2016). Longer as well as shorter sleep durations in old age may thereby be linked with worse health (Jike et al., 2018; Wang et al., 2017), which is in turn associated with lower cognitive performance in some domains (Small et al., 2011; Verhaegen et al., 2003). Because of these known associations, it is important to consider health when studying links between sleep duration and cognitive performance and to test for non-linear associations.

Regarding within-person associations, studies relying on daily life variations in sleep duration observed non-linear effects as well: When people slept longer or shorter than what is usual for them, they showed lower cognitive performance (older adults, general cognitive performance, Gamaldo et al., 2010; children, WM, Könen et al., 2015).

Considering possible particularities in old age, it is important to note that observational studies using late life in contrast to younger samples have not consistently found effects of sleep duration on cognitive function and WM (Devore et al., 2016; Lo et al., 2016). Thus, it remains unclear how everyday variations in sleep duration are associated with WM performance in older adults' daily lives. Nonetheless, we expect that both short and long sleep durations are linked with WM in older adults, which we address in this study by including between- and within-person links with different aspects of WM.

#### **4.1.2 Sleep Duration and WM Improvements**

Apart from daily levels of cognitive performance, sleep also impacts learning and improvement in new skills across different domains such as motor skills (Tucker et al., 2011) or language acquisition (Fenn et al., 2003). Improvements on new tasks by repeated performance (i.e., retest learning) are “a basic form of cognitive plasticity” that remains into old age (L. Yang et al., 2006). Thus, despite general declines in most cognitive domains (Salthouse, 2019), learning still occurs in tasks that are repeated often (L. Yang et al., 2006). Considering retest learning as a reserve that could potentially attenuate cognitive loss in old age (Zihl et al., 2014), respective associations with sleep might be important from a clinical perspective, suggesting sleep interventions to optimize cognitive plasticity based on retest learning. Similarly, interventions aiming to improve sleep have, for example, been suggested to potentially slow the progression of mild cognitive impairment (Bademli et al., 2019; Torossian et al., 2021).

Improvements in performance on WM tasks in particular have been observed in children and young adults after periods of sleep but not after similar-length periods of being awake (Kuriyama et al., 2008; Zinke et al., 2018). In older adults specifically, improvements also occurred after naps and periods of quiet wakefulness (Sattari et al., 2019). This is interpreted as suggesting that in old age, consolidation processes may take place across a variety of conditions that involve as little interference as possible (Mednick et al., 2011; Sattari et al., 2019). Furthermore, among young adults, improvements in a WM task occurred longitudinally across days of normal sleep, but were impeded by prolonged sleep restriction over several nights in a laboratory-based sleep restriction study (van Dongen et al., 2003). This effect was dependent on the amount of sleep restriction, with shorter sleep durations being associated with less improvement. In general, these effects are interpreted as consolidation processes (i.e., learning) without further practice of the task taking place during sleep. However, the concrete processes for improvements in WM performance are not yet known (Kuriyama et al., 2008; Zinke et al., 2018).

To the best of our knowledge, no daily life study has yet addressed associations between sleep duration and improvements in WM performance (practice-related learning) assessed with multiple tests per day across several subsequent days. (For an assessment of longer-term variations in normal sleep duration and practice effects in cognitive tasks performed weekly across several months see Dzierzewski, 2012.) Multiple fine-grained measurements allow for a more precise estimation of mid-term learning improvements on a task, which may be predicted by people’s everyday sleep duration during the learning period. We expect that older adults who sleep more on average would also show greater improvement in a WM updating task that is repeatedly performed within and across study days.

### **4.1.3 Sleep Duration and WM Performance Variability**

Sleep duration may not only impact average levels of cognitive performance and improvements (i.e., learning) but also intra-individual variability in performance, namely (in-)consistencies in WM performance (Adam et al., 2006; Doran et al., 2001). Cognitive variability has typically been assessed as short-term intra-individual variability in reaction times. In general, cognitive variability is higher at lower cognitive performance levels, that is, people with lower cognitive abilities are less stable in their cognitive performance (Lu et al., 2016). Consistent with this finding, older adults showed higher intra-individual variability in reaction times compared with younger adults on several reaction time and decision tasks (Hultsch et al., 2002). However, short-term variability in WM accuracy does not appear to be increased among older compared with younger adults (Fagot et al., 2018; Robertson et al., 2006). A possible reason for this could be that WM accuracy vs. reaction time tasks rely on different scales, with scales for WM accuracy tasks being more coarse and bounded at the upper and lower end, leading to lower sensitivity and potentially floor or ceiling effects in WM accuracy (Fagot et al., 2018). Another contributing factor could be that older adults emphasize accuracy over speed, which may increase variability in reaction times and decrease variability in accuracy (Salthouse, 1979). Variability in cognitive performance has mostly been considered a risk factor, for example for cognitive decline or mortality (Batterham et al., 2014; Lövdén et al., 2007). However, some variability in cognitive performance may be associated with improvements over time when learning new tasks (e.g., as people try out different strategies (Siegler, 1994). Thus, variability may indicate adaptive processes during learning, that is, up to an asymptotic personal level of performance, whereas it could indicate unreliable information processing after this asymptotic level is reached (Allaire & Marsiske, 2005). If so, variability in WM performance controlled for practice-related improvements might be an important indicator for cognitive aging and/or cognitive decline, over and above an individual's general level of performance.

Studies have documented that sleep deprivation increased variability in reaction times in younger but not older adults (Adam et al., 2006; Doran et al., 2001), which could again be due to speed-accuracy trade-offs (Salthouse, 1979), but corresponding research does not yet exist for verbal-numerical WM performance or the role of daily variations in sleep duration. On the one hand, increased variability may mainly result from increased need for sleep following sleep deprivation that leads to attentional lapses (Doran et al., 2001). On the other hand, numerical WM performance is associated with processes involving attention and frontal control that are sensitive to sleep loss and are also relevant for state-instability observed regarding reaction times (Doran et al., 2001). Thus, we expect that reduced sleep is also associated with increased variability of numerical WM performance.

#### **4.1.4 Covariates**

Previous research regarding associations between sleep duration and cognitive performance has treated old age as one age period, although it can span up to 40 years and more. There has been a push to distinguish young-old adults, ca. 60-79 years, and old-old adults, >80 years (P. B. Baltes & Smith, 2003) and the population of old-old adults is increasingly growing (Federal Institute for Population Research [Bundesinstitut für Bevölkerungsforschung] but not yet well studied. In addition, vulnerability potentially increases in old-old age (M. M. Baltes, 1998). Old-old adults may become more vulnerable to the cognitive effects of sleep loss as they experience more generalized declines in functioning (M. M. Baltes, 1998). Furthermore, many chronic illnesses that become increasingly common in old age are risk factors for sleep disturbances (e.g., cardio-vascular disease, chronic pain, depression, (Kuzma et al., 2012) and several sleep characteristics (e.g., sleep phases, efficiency) change in old-old compared with young-old adults (Ohayon et al., 2004) which could in turn moderate effects of sleep duration. Therefore, it is necessary to control for potential differences between the two age groups. In addition to chronological age, some research has also suggested differences with regard to gender (Bocabella & Malouf, 2017) which we will thus adjust for.

Also, health is generally linked with both sleep and cognitive performance. For example, worse physical and mental health are thought to underlie the association of very long sleep with lower cognitive performance (Lo et al., 2016). As such, health status, that is people's physical and mental comorbidities, should be considered when assessing these links in old age. Because depressive symptoms have repeatedly been associated with sleep disturbances (Lippman et al., 2017) and cognitive performance (Shimada et al., 2014) this will be considered as well.

#### **4.1.5 Current Research**

We use repeated daily life assessment data from a sample of older adults to study associations between sleep duration and different aspects of WM performance within and across days, extending previous studies by simultaneously addressing the level of WM performance, learning, and intra-individual variability.

First, we predicted that people who, on average, sleep a lot or very little show lower WM performance compared to people with average sleep duration (H1). Second, we predicted that with longer average sleep duration, people improve more in their WM performance over time (H2). Third, we predicted that with shorter average sleep duration, people show more variable (i.e., less stable) WM performance (H3). Because quadratic effects (i.e., effects of too long as well as too short sleep durations) have been reported for overall WM performance, we also explored quadratic effects of sleep duration on learning and variability. Finally, we tested within-person effects. We

expected that people show lower WM performance on days when they had slept more or less than their personal average compared to days with average sleep duration (H4). Because of potential differences between young-old and old-old adults, we explore age differences in all associations. In addition, we control for participants' gender, health status, and depressive symptoms, which have been linked with both sleep and WM performance.

## 4.2 Methods

### 4.2.1 Sample

This study uses data from 160 older participants of the EMIL study (Emotional Reactivity and Emotion Regulation – A Multi-Timescale Approach Added to ILSE), which included seven days of daily life assessments and a laboratory-based psychological test paradigm. 121 young-old participants (66-69 years old, 52.9% male) born 1950-52 and 39 old-old adults (84-90 years old; 38.5% male) born 1930-32 participated. Most participants were married ( $n = 103$ , 64.4%), some were widowed ( $n = 26$ , 16.3%) or divorced ( $n = 22$ , 13.8%), and a few were single ( $n = 9$ , 5.6%). On average, participants completed 14.2 years ( $SD = 2.5$ ) of formal education. Five participants who never reported on sleep and participated in the WM task for the same assessment day were excluded from the descriptive data and all following analyses.

We recruited all young-old and most of the old-old participants from the Interdisciplinary Longitudinal Study of Adult Development (ILSE; for details on the sample see Sattler et al., 2017), which was conducted in the cities of Heidelberg and Leipzig. To increase statistical power, we further recruited 15 participants from the older age group (born between 1929 and 1935), also from the communities of Heidelberg and Leipzig, via advertisements in local newspapers. As described in another study using this sample (Schilling et al., 2022), higher cognitive functioning at the previous T4-wave of ILSE (2014-2017) was the main predictor for taking part in the EMIL study.

### 4.2.2 Procedure

Participants were contacted by mail and by phone. Before participating, they provided informed consent. Participants received 125€ for full participation in the laboratory (not relevant to the present manuscript) and the repeated daily life assessments. Data were collected between March 2018 and August 2019 in the regions of Leipzig and Heidelberg, Germany. The project was approved by the ethics committees of the University of Heidelberg and the German Society for Psychology (DGPs).

This study only uses data from the repeated daily life assessments (for details on the complete study, see <https://osf.io/qr93g>; data are available from the authors upon request). The ambulatory assessment study was conducted using touch-screen tablets (Apple iPads) that we

provided to the participants. Every momentary assessment included questions on current affect and stress experiences and two trials of a WM task. In the first assessment each morning, participants additionally answered questions about the previous night's sleep. Research assistants explained to participants how to use the iPad and participants tried the different kinds of questions under the supervision of the research assistant, in particular the WM task. They performed ten trials of the WM task to ensure they had understood the task well.

The ensuing seven-day assessment period was chosen by the participants as a typical week. We scheduled a phone call on the second day and offered continuous phone support. Every day, participants answered up to six brief questionnaires. They filled out the first questionnaire after waking (i.e., self-initiated); the further assessments were prompted to be filled out at 10am, 1pm, 4pm, 7pm, and 9pm. To accommodate participants' daily schedules, they could also fill out the questionnaire anytime between 30 minutes before and two hours after the scheduled time. Based on previous work, 2- to 3-hour intervals were chosen to assess daily life challenges (Wrzus et al., 2013) and to model the circadian rhythms of saliva cortisol (Chui et al., 2014; Hoppmann et al., 2018) that was also included in the larger assessment battery, but not considered in this report. The assessment schedule is illustrated in Figure 4.1a.

Assessments containing all relevant data were obtained for a total of 1,097 days and 6,369 assessments. Adherence to the study protocol was very high: On average, participants provided data on 6.86 ( $SD = 0.65$ ) of the seven days and responded to 5.81 ( $SD = 0.54$ ) of the six assessments per day. The number of completed assessments did not differ significantly between the young-old and old-old age group,  $t(49.92) = 1.24$ ,  $p = .22$ .

### **4.2.3 Measures**

#### *Sleep Reports*

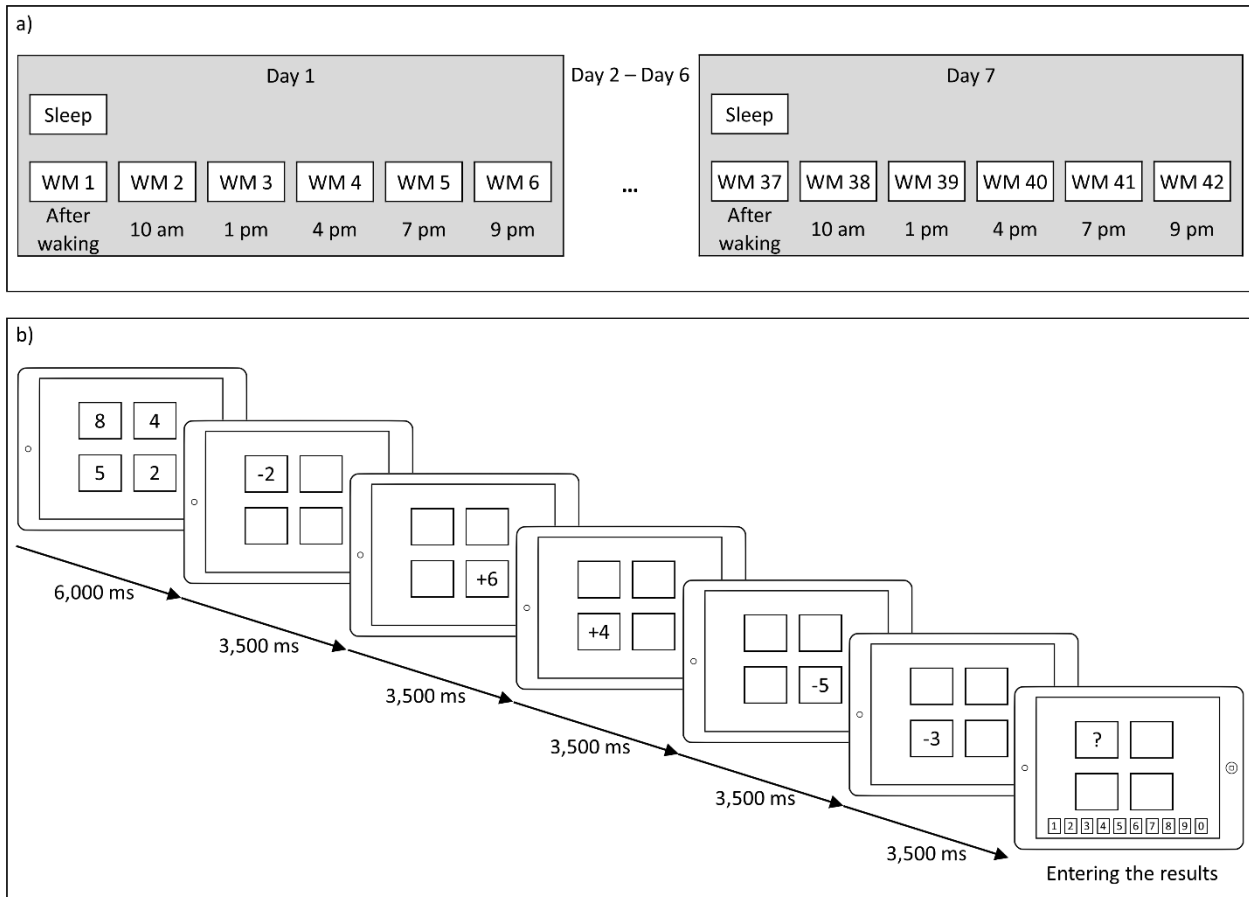
In the first assessment after waking each morning, participants answered questions regarding their sleep the previous night. Participants reported their sleep duration ("How many hours did you actually sleep?") in hours and minutes. Using self-reports of sleep duration is common in the literature (Gamaldo et al., 2010; Könen et al., 2015).

#### *WM Updating Task*

Participants worked on two trials of a numerical updating task at the end of each momentary assessment. This task has been successfully used in previous ambulatory assessment and intensive longitudinal research also including older participants (Riediger et al., 2011; Shing et al., 2012) and is a valid indicator of a general WM factor, comparable to complex-span tasks (Schmiedek et al., 2009). The task is illustrated in Figure 4.1b.

**Figure 4.1.**

Illustration of (a) the Assessment Schedule and (b) the Working-Memory Updating Task.



Four digits between 0 and 9 were presented in a 2x2 grid for 6,000 ms, then disappeared. Thereafter, five updating operations appeared consecutively in the cells of the grid for 3,500 ms each, which had to be applied to the initially displayed number or intermediate result. The operations were subtractions or additions ranging from  $-8$  to  $+8$ , with all results (intermediate and final) ranging from 0 to 9. The operations were randomly assigned to the four cells, but no cell had an operation displayed twice in a row. After all updating operations, participants entered the final results for each of the four cells. They could correct their entries, if necessary. When participants confirmed their entries, they received color-coded feedback with correct responses highlighted in green while incorrect responses were shaded in grey. We used the proportion of correct responses averaged across both trials as an indicator of momentary WM performance (i.e., percentage of correct responses out of eight numbers). To obtain reliability estimates, we conducted a two-level confirmatory factor analysis. Omega total (McNeish, 2018) was .613 for within-person reliability and .998 for between-person reliability. These values are comparable to those reported in previous research using this task (Dirk & Schmiedek, 2016).



### *Health Status and Depressive Symptoms*

We assessed participants' health status as the sum of chronic illnesses as indicated by participants on the multimorbidity list which contains 36 different physical and mental health conditions ("yes" = 1, "no" = 0; e.g., myocardial infarction, osteoarthritis, diabetes). This measure was adapted from the Charlson comorbidity index (Charlson et al., 1987; Knoll et al., 2020b). (For the full list of conditions see study materials at <https://osf.io/qr93g>). Depressive symptoms were assessed with the Zung Self-Rating Depression Scale (Zung, 1965). Participants rated 20 statements (e.g., "I feel downhearted and blue.") regarding how often they applied to them over the last weeks on a four-point scale from 1 (*none or a little of the time*) to 4 (*most of the time*). These responses were used to create a sum score, with higher values indicating higher symptom load. We used the score as a continuous control variable because the scale contains symptoms common in old age (e.g., problems concentrating, digestive problems) and standard cut-offs may not apply.

#### **4.2.4 Analytic Strategy**

We used R Studio (Version 1.4; RStudio Team, 2021) and Mplus (Version 8.3; L. K. Muthén & Muthén, 1998-2017) for data analysis. In Mplus we conducted mixed-effects (multilevel) models to analyze the repeated assessments nested within participants. In particular, for the between-person hypotheses we specified a two-level location-scale model (McNeish, 2020). Thus, individuals could differ in initial levels of WM performance (random intercepts), as well as in the individual learning curves (random slopes). In addition, location-scale models allow for heterogeneous variances (i.e., person-specific within-person residual variances), which may be defined and analyzed as between-person latent variables. For the within-person hypotheses, we specified a three-level mixed-effects model with random intercepts (WM levels varying between days and between persons) and random slopes (associations between sleep and WM varying between persons). Equations for the models can be found in the supplement (SI) and all analysis scripts can be found at <https://osf.io/qr93g>.

#### *Estimation*

Location-scale models implemented in Mplus use the Bayes estimator with Markov Chain Monte Carlo (MCMC) methods. We used the Mplus default diffuse priors in all models (for details see Asparouhov & Muthén, 2010). The estimation used two chains and we determined convergence using the Gelman-Rubin diagnostic criterion with values close to one indicating that the between-chain variance is small compared to the within-chain variances (B. Muthén & Asparouhov, 2012). Between-person models were run for at least 10,000 iterations and within-person models for at least 30,000 iterations. The first half of the iterations was used as burn-in and the second half was used to estimate the posterior distribution. With regard to missing data treatment, the algorithm

provides full information estimation unbiased under missing at random (Asparouhov & Muthén, 2010).

#### *Sleep Duration Predicting WM, Variability, and Improvement (Between-Person)*

First, we assessed how to best model the individual WM learning curves across the assessment period. Visual inspection and model comparisons by means of the deviance information criterion and  $R^2$ s indicated that a log-linear increase described the improvements better than a linear increase. Thus, we used the natural logarithm of the number of the WM assessment (i.e., the within-person count of the assessment across beeps and days, starting at 1 for the first assessment at the first study day) as the random within-person predictor of WM, hence modeling a log-linear curve of WM performance improvement across repeated trials of the task for each person.

We specified a two-level location-scale model (McNeish, 2020) to analyze how sleep duration predicted initial levels, learning improvements, and variability of WM performance. That is, the model included the average sleep duration across the study days as a between-person-predictor of the random intercept (corresponding to the predicted initial level of WM), the random slope of the log-linear learning curve (indicating the learning improvements in WM performance across repeated assessments), and the within-person residual variance. This within-person residual variance mirrors the within-person variability of WM performance that is not attributable to learning improvements and will be referred to as variability in the following. We tested curvilinear effects of sleep duration, including duration and duration-squared as predictors. Sleep duration was grand-mean centered when computing the linear term and the quadratic term.

Because the sample consisted of two distinct age groups (young-old, 66-69 years old, and old-old, 84-89 years old), we also included participants' age group as an additional predictor for the random intercept to account for age-related decline in WM capacity. Age group (originally coded as young-old = 0 and old-old = 1) was grand-mean centered so that the model estimates refer to the overall sample and the age group effect shows the mean difference between the two groups.

#### *Sleep Duration Predicting Variations in WM (Within-Person)*

To analyze within-person associations between within-person variation in sleep duration and momentary WM performance, we specified a separate three-level model comprising assessments within-days within-persons (Level 1), days within-persons (Level 2), and persons (Level 3). This model focused on day-to-day changes in sleep duration and WM performance and thus did not include the learning curve or within-person variability across the study.

In this model, the Level 2 intercepts (i.e., the latent daily means of WM performance, one score for each person per day) were the dependent variable of interest. Using latent instead of manifest daily means is preferable from a statistical standpoint because it accounts for reliability

and the number of measurements. The Level 2 intercepts of WM were predicted by person-mean-centered sleep duration and duration-squared as Level 2 predictors with random slopes, i.e., the associations could vary between people. However, deviations from one's mean sleep duration may have different implications for WM performance depending on the level of one's personal mean. For example, sleeping two hours more than usual may still be beneficial for someone who sleeps an average of only five hours whereas it may be detrimental for someone who sleeps an average of seven or eight hours. Hua et al., 2020 To account for this, we also included people's average sleep duration as a between-person moderator of the within-person associations between sleep and WM performance. Average sleep duration was grand-mean centered. Age group was also grand-mean centered and included as a between-person predictor for the intercept.

#### *Additional Analyses*

To assess whether associations between sleep and WM differed between young-old and old-old participants, we repeated the previous analyses with age group as a moderator of all associations (in addition to being a predictor for the intercept in the main models). Additionally, we estimated models including participants' gender, health status (number of chronic illnesses) and depressive symptoms as between-person predictors for WM performance in the main models. All between-person predictors were centered on their respective grand-means (i.e., sample averages).

**Table 4.1**

Descriptive Statistics and Correlations for Sleep Duration, Working-Memory, Number of Assessment and Age Group. Within-Person Correlations Below, Between-Person Correlations Above the Center Diagonal.

	Mean (SD)	iSD	ICC	Correlations					
				Sleep duration	WM	No. of assessment	Health status	Depressive symptoms	Age group
Sleep duration <sup>a</sup>	6.74 (1.02)	0.74	0.582	-	0.183*	-0.004	-0.248*	-0.155	-0.026
Working-memory <sup>b</sup>	62.36 (27.62)	17.12	0.577	.043*	-	-0.123	-0.246*	-0.192*	-0.441*
No. of Assessments <sup>c</sup>	39.73 (5.75)	-	-	.010*	.288*	-	0.094	0.048	0.037
Health status <sup>d</sup>	4.38 (3.30)	-	-	-	-	-	-	0.492*	0.381*
Depressive symptoms <sup>e</sup>	33.68 (7.67)	-	-	-	-	-	-	-	0.181*

*Note.* iSD = intra-individual standard deviation. ICC = intraclass correlation coefficient, i.e., proportion within/overall variance.

<sup>a</sup> Self-reported sleep duration in hours. <sup>b</sup> Working-memory performance in %. <sup>c</sup> Participants could provide data for a maximum of 42 assessments. <sup>d</sup> Number of chronic conditions (max. 36, see (Knoll et al., 2020b)). <sup>e</sup> Assessed with the Zung Self-Rating Depression Scale (Zung, 1965)

\* $p < .05$

## 4.3 Results

### 4.3.1 Descriptive Statistics and Zero-Order-Associations

Table 4.1 shows descriptive statistics and intercorrelations of the variables of interest across the whole sample. Descriptive statistics for each of the two age groups separately are reported in the Supplement (Table S2). On average, participants slept 6.7 hours per night and had 62.4% correct answers on the WM task. As indicated by the intra-class correlation coefficients (ICCs) and intra-individual standard deviations (iSDs), substantial within- and between-person variance was observed in both WM performance and sleep duration, thus warranting analyses at both levels. On the within-person level, longer sleep duration was associated with somewhat higher WM performance. Additionally, WM was higher with increasing number of measurement occasions, pointing to within-person improvement over time. At the between-person level, sleep duration and WM performance were also positively linked.

### 4.3.2 Between-Person Associations of Sleep Duration and WM

The model results are reported in Table 4.2. To enhance interpretability, we will mainly discuss unstandardized effects, but we provide standardized estimates (Hoffman & Stawski, 2009) for the main parameters of interest in the text. First, the estimated average WM performance at the beginning of the study was about 48.6% accuracy (Intercept WM) and results showed that participants significantly improved across time (i.e., learning, Table 4.2 and Figure 4.2). Additionally, people who started with a lower level of WM tended to improve more across the study (i.e., they had steeper learning curves). Importantly, there was still substantial intra-individual variability not accounted for by participants' improvement over time (i.e., variability). Participants in the older age group started out with lower WM performance on average (note that the WM intercept corresponds to the total sample average and the effect of age group is the mean difference between the two groups).

Regarding associations with sleep, results showed that participants' estimated initial WM performance level (i.e., the random intercept) was quadratically ( $b = -2.872$ , standardized  $\beta = -.152$ ) associated with their average sleep duration (Table 4.2). As predicted and visualized in Figure 4.3 both shorter and longer sleep durations were linked with lower WM performance.

The learning curve slope (i.e., increase in WM performance) was non-linearly associated with average sleep duration (Table 4.2,  $b = 0.762$ , standardized  $\beta = .189$ ). To illustrate these associations, we plotted the predicted learning trajectories over time for different average sleep durations. As can be seen in Figure 4.2, people sleeping an average of 5.7 hours (i.e., 1 SD less than the mean) started at a lower initial level, and despite their somewhat steeper learning curve were

predicted to reach the lowest final level. People sleeping 7.7 hours (i.e., 1 SD more than the mean) also had a steeper learning curve and were predicted to reach the highest final performance level. In contrast to our assumptions, intra-individual variability in WM performance was not significantly associated with sleep duration, nor was it associated with sleep duration squared (Table 4.2).

**Table 4.2**

Between-Person: Sleep Duration Predicting Working-Memory, Learning, and Variability.

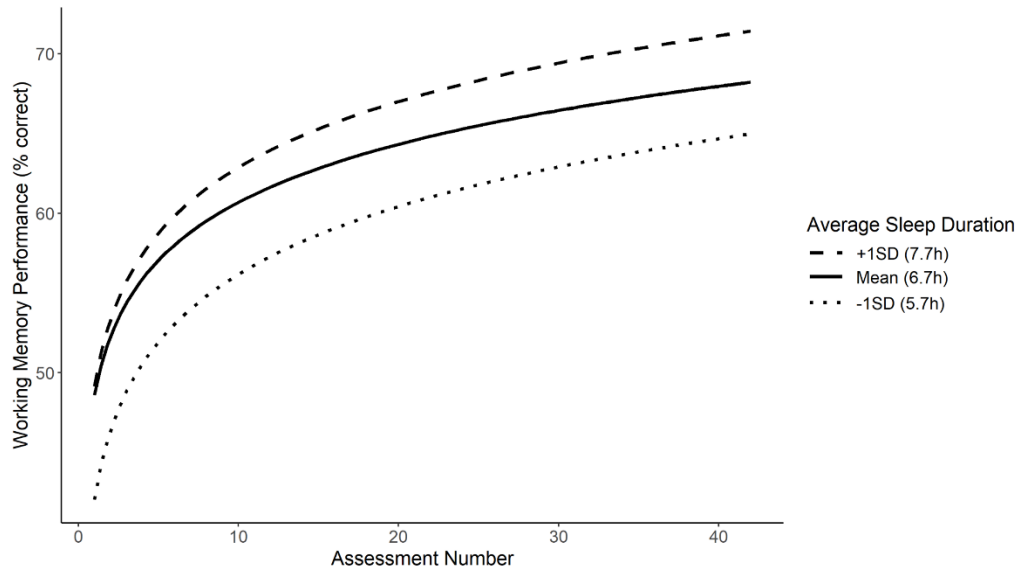
	Estimate	95% CI
Intercept WM	48.585*	[44.293, 52.891]
Learning Curve <sup>a</sup>	5.254*	[4.175, 6.303]
Variability	5.472*	[5.357, 5.587]
Intercept WM with learning	-50.953*	[-79.003, -29.134]
WM on sleep	3.485	[-0.198, 7.039]
WM on sleep <sup>2</sup>	-2.872*	[-5.029, -0.722]
WM on age group	-22.293*	[-29.122, -15.34]
Learning on sleep	-0.086	[-0.969, 0.809]
Learning on sleep <sup>2</sup>	0.762*	[0.236, 1.295]
Variability on sleep	0.023	[-0.075, 0.123]
Variability on sleep <sup>2</sup>	0.011	[-0.047, 0.07]
<b>Random Variances</b>		
WM	458.959*	[354.497, 596.754]
Variability	23.131*	[16.622, 32.138]
Learning	0.339*	[0.261, 0.445]

*Note.* WM = Working-memory, range = 0–100. Variability = Natural logarithm of the within-person residual variance. Sleep = sleep duration in hours. Sleep and age group were centered on their grand-mean. CI = Bayesian credible interval.  $N_{\text{Level1}} = 6430$ ,  $N_{\text{Level2}} = 160$ .

<sup>a</sup> Learning is conceptualized as the within-person (random) slope of WM regressed on the natural logarithm of the assessment number.

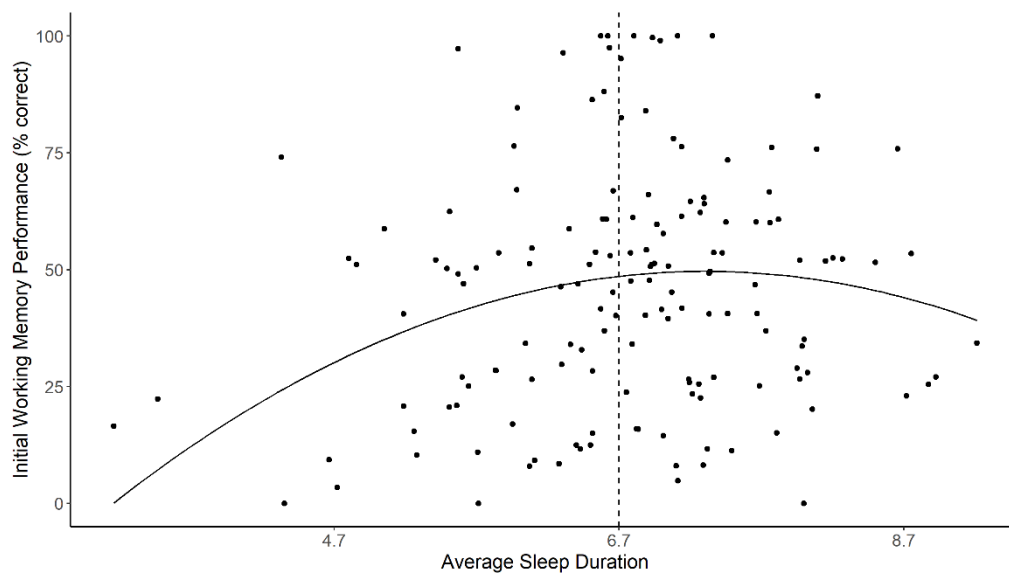
\* $p < .05$

**Figure 4.2**  
 Predicted Learning Curves for Average Different Sleep Durations.



*Note.* This figure indicates that both people who slept longer and those who slept shorter than the average of 6.7h showed more practice-related improvements (i.e., learning) than people with average sleep duration. It can be obtained that people who slept longer than the average were predicted to reach the highest asymptotic level, whereas people who slept shorter than the average were predicted to reach the lowest asymptotic level, despite experiencing more practice-related improvements.

**Figure 4.3**  
 Association Between Average Sleep Duration and the Initial Level of Working-Memory.



*Note.* The dotted line represents the mean overall sleep duration of 6.7 hours across the whole sample. It can be obtained that people with sleep durations substantially longer or shorter than 6.7h showed lower initial working-memory performance.

### 4.3.3 Within-Person Associations of Sleep Duration and WM

On the within-person level, sleeping more or less than on other days was on average not significantly associated with WM performance (see Table 4.3). However, there were substantial individual differences in this association (see Table 4.3, Random Variances, WM on sleep/sleep<sup>2</sup>), and average sleep duration significantly moderated the linear association between daily sleep and WM performance ( $b = -1.125$ , Table 4.3). That is, between-person differences in within-person associations existed, depending on participants' average sleep duration: Simple slopes analyses indicated that for people sleeping one hour less (-1SD, 5.7h) than the average participant, sleeping less than usual for them on certain days was significantly associated with lower WM performance ( $b = 1.851$ ,  $p = 0.003$ ; standardized  $\beta = .273$ ). For people sleeping one hour more (+1SD, 7.7h) than the average participant, differences in sleep duration were not significantly associated with WM performance ( $b = -0.309$ ,  $p = 0.339$ ; standardized  $\beta = -.046$ ). These associations are visualized in Figure 4.4.

**Table 4.3**

Within-Person: Variations in Sleep Duration Predicting Variations in Working-Memory.

	Estimate	95% CI
Intercept WM	62.617*	[59.642, 65.552]
WM on sleep (within person)	0.783	[-0.252, 1.764]
WM on sleep <sup>2</sup> (within person)	-0.422	[-1.188, 0.204]
WM on mean sleep (between)	3.684*	[0.769, 6.633]
WM on mean sleep x sleep	-1.125*	[-2.102, -0.145]
WM on mean sleep x sleep <sup>2</sup>	-0.338	[-0.822, 0.199]
WM on age group	-22.113*	[-28.817, -15.306]
<b>Random Variances</b>		
WM within day	262.405*	[252.607, 272.689]
WM between day	64.795*	[54.408, 76.440]
WM between	335.142*	[266.811, 425.919]
WM on sleep	7.587*	[1.165, 17.462]
WM on sleep <sup>2</sup>	0.255*	[0.008, 1.946]

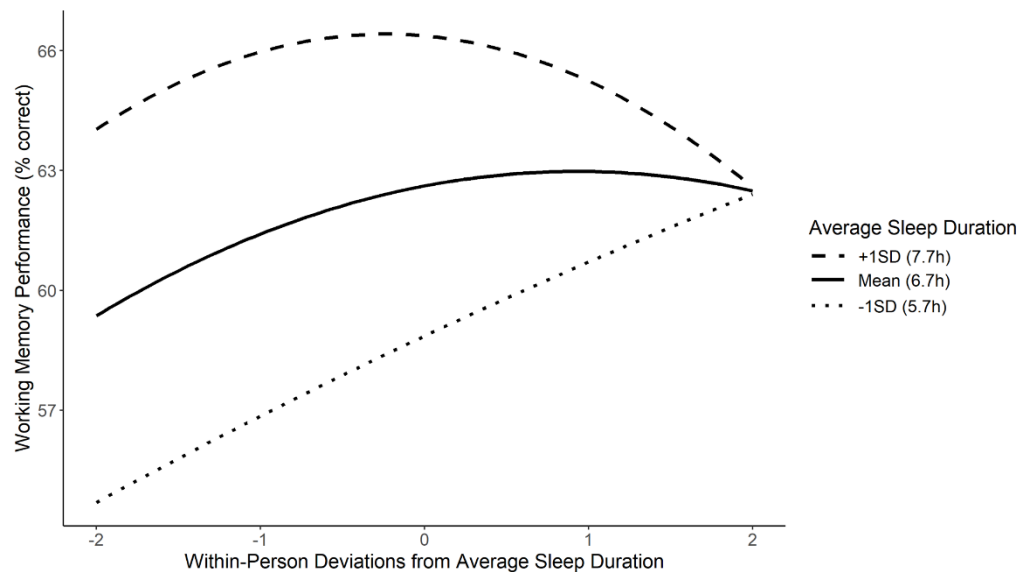
Note. WM = Working-memory, range = 0–100. Sleep = sleep duration in hours; within-person, centered on person-mean. Mean Sleep = Person-mean, centered on grand-mean. Age group was centered on the grand-mean. CI = Bayesian credible interval.  $N_{\text{Level1}} = 6369$ ,  $N_{\text{Level2}} = 1097$ ,  $N_{\text{Level3}} = 160$ .

\* $p < .05$



**Figure 4.4**

Within Person Associations Between Variations in Sleep Duration (Deviations from the Personal Mean) and Working-Memory (Slopes) for Different Mean Sleep Durations.



*Note.* 97 % of data points were variations between sleeping two hours less and two hours more than usual. This figure illustrates that within-person variations in sleep duration had different associations with working-memory performance for people with different average sleep durations. For people with short average sleep durations ( $-1$  SD), working-memory performance was lower on days with shorter than average sleep, yet higher on days with longer than average sleep. Differences in working memory performance for different average sleep durations were not discernible when people slept two hours longer than usual for them.

#### 4.3.4 Additional Analyses

In additional analyses, we assessed whether associations between sleep duration and WM differed between young-old and old-old adults. As in the main models, young-old participants showed a significantly higher initial level of WM performance than old-old participants. However, adults from the two age groups did not significantly differ in their learning improvements or variability, nor did they differ substantially in the associations between sleep duration and WM performance in either the between-person or the within-person models. We report full results for these models in the Supplement (Tables S3 and S4).

Furthermore, we assessed whether participants' gender, health, or depressive symptoms were linked with their WM performance. In the between-person analyses, neither the number of chronic illnesses nor depressive symptoms predicted participants' initial WM performance. However, on average, men started out with a higher level of WM performance than women. None of the parameters of interest changed directionality or statistical significance when adjusting for these covariates (Table S5). In the within-person model, the number of chronic illnesses and depressive symptoms did not predict WM performance either and none of the other parameters

changed directionality or statistical significance (Table S6). For full model results see Supplementary Tables S5 and S6.

#### **4.4 Discussion**

In this study, we examined associations between daily sleep duration and different indicators of WM performance, that is, initial level, practice-related improvement, and moment-to-moment variability in WM performance in older adults' daily life. The study design maximizes ecological validity by assessing sleep and WM as older adults went about their daily routines which makes the results relevant for researchers and clinicians alike. The results support hypothesis H1 and showed that with longer average sleep duration, people showed higher initial performance on a WM task, but with very long sleep duration (for this age group) initial performance was lower. Contrary to hypothesis H2, not only people who slept more but also people who slept less than an average of 6.7 hours per night experienced more improvements (i.e., steeper learning curves) across one week, which might partially be explained by starting from a lower initial level of cognitive performance (which we discuss below). Unexpectedly, people's average sleep duration was not significantly associated with variability in their WM performance over assessments and days (not supporting H3).

In contrast to previous research and hypothesis H4, we found no linear or quadratic effect of within-person deviations in sleep duration for the general sample. However, average sleep duration moderated the within-person coupling of sleep duration and WM performance: Sleeping less than usual was detrimental for people who slept rather short on average (5.7h, one SD below the mean) whereas it had no significant effect for people who slept longer on average (7.7h, one SD above the mean). Neither including participants' age group or gender, nor their health status or depressive symptoms significantly modified any of the associations.

##### **4.4.1 *Between-Person Links of Sleep Durations with Initial Performance and Learning***

The results regarding initial WM performance align with previous research that people with a typical (i.e., average) sleep duration perform higher on WM as well as other cognitive tasks. (Lo et al., 2016). Sleeping less than a certain amount likely leads to reduced vigilance and attention and impaired higher-order cognitive functioning (Frenda & Fenn, 2016), which have been shown to accumulate over time (Doran et al., 2001) and could thus explain why people who sleep less on average started out with lower levels of WM performance. In contrast, sleeping much more than "normal" in old age has been associated with worse health (Jike et al., 2018). However, this was on average not observed in the current study. Additionally, including health status and depressive symptoms in the models did not substantially change the results.

With regard to learning, both people who slept more and people who slept less than the average amount of 6.7 hours, improved *more* across the week of the study (i.e., they had steeper learning curves). Previous research has, to the best of our knowledge, not assessed non-linear associations of sleep duration with learning in WM tasks. One explanation could be related to people's initial levels of WM performance: People who slept very little (or very long) on average started at lower initial performance levels and might have had more potential for learning and improvement. This association between initial level and learning (i.e., steepness of the learning curve) has been documented before: For example, people who started with lower cognitive levels improved more during a cognitive training intervention (Jaeggi et al., 2008), but many results also point in the opposite direction (L. Yang et al., 2006; Zinke et al., 2018).

If people who, on average, slept less at night also took more naps during the day, as suggested in the literature (Häusler et al., 2019) this may also explain the shape of the quadratic effect of sleep duration on the learning curve: Research showed that older adults' cognitive performance improved during naps and more general "down time" (Sattari et al., 2019). One might speculate that those people who slept very little but napped during the day thus also experienced improvements from their naps and not just their nightly sleep. We did not record information on naps in this study and cannot address this explanation empirically. Whether daily and nightly sleep interact in predicting practice-related learning in old age may be interesting to examine in further studies.

Regarding long sleep, these results indicate that older adults who sleep more than their peers are not necessarily at risk for problems with cognitive performance and, at least with regard to learning a new task, they may even have an advantage. One reason for this may be that in contrast to our assumptions, it was only shorter, but not longer sleep duration, that was associated with worse health in this study. Whereas research has shown reduced sleep-dependent consolidation in old age for some functions (e.g., prospective memory, Leong et al., 2021; declarative memory, Gui et al., 2017), for WM tasks specifically research has indicated that older adults can even benefit from naps and periods of quiet wakefulness to improve (Sattari et al., 2019). Our results additionally suggest that they could also benefit from longer sleep durations for practice-related improvements in a WM task. However, future research may assess whether the advantages people with longer sleep durations showed with regard to learning persist in the long-term. Furthermore, the average sleep duration of 6.7h observed in this study is both shorter than in a representative sample of the German population over 60 (7.1h, Piper, 2016) and shorter than recommended for optimal functioning (7–8h, Hirshkowitz et al., 2015). Thus, it is also possible that sleeping significantly more than recommended (i.e., more than 8h) may still be detrimental to learning processes. Overall, these results suggest that it may be relevant to also address sleep when older adults experience

cognitive impairments.

In contrast to our assumptions regarding variability of cognitive performance, people's average sleep duration did not predict how variable (vs. consistent) their WM performance was. This may be because we studied normal variations in daily sleep duration, whereas previous research, which observed associations between reduced sleep and increased variability, relied on total sleep deprivation (Doran et al., 2001). Processes thought to be the cause of this increased variability following sleep loss, such as state instability, may thus not occur within normal variations of daily sleep duration but only under more extreme conditions. Additionally, we assessed variability in WM accuracy whereas previous research relied on reaction time variability (Doran et al., 2001). As previously discussed, accuracy measures may be less sensitive to detect variability as a result of differing sleep duration because their scale is more coarse than that for reaction times (Fagot et al., 2018). In addition, age-specific speed-accuracy trade-offs could explain these differing results for older adults specifically (Salthouse, 1979). It would be interesting for future research to assess whether the same results are found for younger adults. Furthermore, other situational factors may be (more) relevant in explaining the variability we did observe. For example, previous research has shown that WM performance varies with motivation and affective states (Brose et al., 2012; Riediger et al., 2011), which we did not address in the current report. In addition, we assessed variability using scores averaged across two trials and have thus reduced the within-person variability at the fastest observed level (i.e., trial-to-trial) by aggregation.

#### **4.4.2 *Within-Person Links Depend on Average Sleep Duration***

In contrast to previous studies (Gamaldo et al., 2010; Könen et al., 2015), we did not observe consistent within-person couplings between sleep duration and WM performance. A reason for this could be the effort exerted by participants. Neuro-imaging studies have shown increased frontal activation in sleep deprived/sleep restricted vs. well-rested participants when working on interesting and challenging tasks (Frenda & Fenn, 2016). Thus, people could have partially compensated for potential impairments following nights with little sleep by exerting more effort. However, this may only be possible to a certain degree. When considering people's average sleep duration, results indicated that people who slept little on average experienced lower WM performance on days when they had slept less than usual the night before, whereas this effect was not significant for people with average or above average general sleep duration. This suggests, within-person variations may be more relevant for people already sleep deprived. This is in line with research indicating that more extreme levels of sleep restriction led to stronger effects on cognition (van Dongen et al., 2003). However, on average, people in the current study did not vary tremendously in their sleep duration across one week, so the study may have been lacking in

variability to find more substantial average within-person effects.

#### **4.4.3 Limitations**

In closing, we note limitations of the study. First, participants included in this report represent a positively selected sample of old and very old adults. As previous studies demonstrated, higher cognitive functioning was the main predictor for participants of the longitudinal ILSE study taking part in this study (Schilling et al., 2022), thus limiting the generalizability to the general “old age population.” Furthermore, the sample is relatively highly educated, which could be a protective factor with regard to cognitive performance in old age (Opdebeeck et al., 2016). As such, the associations found between sleep and WM here may even underestimate those in the general population. Similarly, especially the sample of old-old adults was rather small, limiting the power to detect age differences in couplings of sleep and WM performance. Still, we replicated known differences in average cognitive performance and health between young-old and old-old adults. If feasible, considering the difficulty of recruiting very old participants for intensive study designs, future research may consider using a larger sample of old-old adults to replicate the findings presented here.

Second, the results indicated that the within-person reliability of the WM tasks was not very high, but comparable to other research using WM assessments in daily life (Dirk & Schmiedek, 2016), whereas it was very high on the between-person level. Thus, for the between-person parts of the study, the repeated measurements increase the reliability for the mainly studied between-person associations, whereas the effects for within-person associations may even have been underestimated due to lower reliability.

Third, the results of the current study have to be interpreted considering its measurements. The WM task included only two trials per assessment and sleep duration was self-reported by participants. Despite these being common approaches for studying these phenomena (Gamaldo et al., 2010; Riediger et al., 2014), future research could include WM performance measured both in daily life and in the lab and sleep duration measured using actigraphy to determine whether there are differential effects. Self-reports differ from other sleep measures (Zinkhan et al., 2014); differential and independent effects have, for example, been observed regarding links between different sleep measures and affect or functional limitations (Konjarski et al., 2018; Teas & Friedman, 2021). Thus, differential effects of self-reports versus other measures of sleep could also be considered regarding WM performance. Finally, we did not assess whether people took naps during the days of the study, which could have influenced the results, as some studies have shown that older adults experience improvements on cognitive tasks following naps as well as general “down time” (Cox et al., 2019; Sattari et al., 2019).

#### **4.4.4 Conclusion**

This study showed that daily sleep was linked to different aspects of daily WM performance also late in life. Relatively short and relatively long average sleep was linked to lower initial cognitive performance on a relatively new WM task. These initial differences could be compensated through practice (i.e., learning) among people with longer sleep duration. People with short average sleep showed steeper learning compared to people with average sleep duration but did on average not reach the same level as people sleeping longer. In addition, older adults' momentary WM performance may be relatively "immune" to daily within-person variations in sleep duration, unless shorter sleep occurs among people with already short general sleep durations. In sum, sufficient sleep still seems to be important late in life, when cognitive performance and sleep generally worsen and it is relevant to include different aspects of cognitive performance, because long and short sleep may differentially impact initial levels of performance vs. learning.

## CHAPTER 5

### General Discussion

The results in the chapters of this dissertation showed that older adults' sleep has important links with affective, health-related, and cognitive functioning in their daily lives. Variations in sleep quality predicted emotional well-being and health perceptions and sleep duration was linked with cognitive functioning. Considering the opposite direction of daily functioning predicting subsequent sleep, only affective reactivity and self-rated health were associated with subsequent sleep quality. Interestingly, these associations did not consistently vary between young-old and old-old adults. In the next sections I first discuss the results from this dissertation as they relate to the research questions. Second, I consider strengths and limitations, addressing future research directions. Third, I discuss implications of the results, including considerations on potential avenues for interventions.

#### **5.1 (Bidirectional) Links Between Sleep and Different Aspects of Functioning**

##### ***5.1.1 Sleep Predicts Affective and Health Functioning and Partially Vice Versa***

The results from Chapter 2 and Chapter 3 partially support bidirectional links between sleep quality and next day affective functioning and health. Worse sleep quality predicted stronger next day baseline NA, which might be considered something along the lines of bad mood (Kaufmann et al., 2020). Similarly, worse sleep quality was linked with increased next day pain and lower self-rated health. However, regarding the opposite direction, only less affective reactivity, which might indicate better emotion regulation, and better self-rated health, an overall rating of well-being (Pinquart, 2001b), also predicted better next night sleep quality. These findings partially align with previous research which generally supported predictive effects of sleep quality on subsequent affect and pain (Afolalu et al., 2018; Konjarski et al., 2018). They add to previous research, indicating that sleep and self-rated health are not only cross-sectionally linked (Burke et al., 2012; Simoes Maria et al., 2020) but predict each other from day to day. The results furthermore support the hypothesis that emotion regulation, as determined by affective reactivity, could be the relevant factor linking affective functioning with next night sleep quality and may thus potentially explain previous mixed results when affective reactivity was not considered.

Interestingly, links between previous night sleep quality and next day baseline NA paralleled links with next day health perceptions which may suggest potential overlap in these effects. Because both pain and self-rated health also have affective components (Raja et al., 2020; Winter et al., 2007) several associations deserve attention to integrate these findings. Pain is associated with increased subsequent NA (Frumkin & Rodebaugh, 2021) but stronger NA has also been linked with

aggravated subsequent pain and decreased subjective health (Paquet et al., 2005; Segerstrom, 2014; Tang et al., 2008). Considering sleep, stronger NA has been suggested as a mediator for links between poor sleep and increased pain (O'Brien et al., 2010). On the other hand, sleep quality has also been shown to moderate links between pain and NA (Hamilton et al., 2007). Because of limitations in research designs, it remains open how exactly NA is associated with health perceptions and their links with sleep. More fine-grained temporal analyses are needed to clarify the temporal ordering of associations between sleep, NA, and health perceptions. For now, one might conclude that sleep predicts both affective and physical aspects of well-being and that these effects may be intertwined.

In contrast to baseline NA and health perceptions, sleep quality did not predict affective reactivity. One could interpret modest increases in NA and pain as well as decreases in self-rated health as decrements in well-being. Thus, instead of amplifying affective reactivity, low sleep quality may mainly result in diffuse discomfort and thus lower overall well-being the next day. However, it is also possible that following nights with bad sleep, older adults may choose to avoid potentially stressful situations (Charles & Luong, 2013) which could prevent observations of increased affective reactivity.

Regarding the opposite direction, affective reactivity and self-rated health, but not baseline NA or pain, predicted next night sleep quality. It is possible that considering affective appraisals of pain could have resulted in mirrored findings (Affleck et al., 1996). Both NA and depressed mood have been suggested as mediators of the link between pain and subsequent sleep (Nicassio et al., 2012; Valrie et al., 2008). Not having considered appraisals of pain could potentially explain inconsistent previous results regarding effects of pain on sleep. For example, pain may be linked with increased cognitive-emotional arousal, which could lead to reduced sleep quality if it is not successfully regulated (Smith et al., 2000; Tang & Harvey, 2004; Tousignant et al., 2019). Considering overlaps with NA and affective reactivity, emotion regulation could thus also play a role in linking pain and subsequent sleep quality. Emotion regulation can help people cope with pain (Paquet et al., 2005) and may be a crucial factor for good sleep quality (Babson, 2015; Espie, 2002). In order to clarify whether affective reactions and successful emotion regulation following pain predict subsequent sleep, knowing more about people's evaluations of pain during the day could be helpful.

If emotion regulation is the central aspect linking daily functioning with sleep quality, one might ask how self-rated health predicts sleep. On the one hand, increased stress has been shown to predict lower self-rated health (Barry et al., 2021), so this overall assessment people make about their health may already include aspects of affective reactivity. On the other hand, it is possible that self-rated health captures general dysregulation in physical systems, such as HPA axis activity or



increased inflammation (Christian et al., 2011; Dahlgren et al., 2009), which may then also impact subsequent sleep quality. Overall, sleep quality predicted daily affective well-being and health but may be relatively immune to smaller daily variations in baseline NA or pain.

### **5.1.2 Sleep Duration and Different Aspects of Cognitive Functioning**

Turning from affective functioning and health perceptions to cognitive functioning, the results from Chapter 4 showed associations between sleep duration and different aspects of working memory performance. As in previous research, both very short and very long average sleep duration (between-person) were associated with lower levels of performance in a new task (Lo et al., 2016). Additionally, average sleep duration was linked with retest learning: Participants with very long and very short sleep durations tended to improve more across the week than did participants with average sleep durations, resulting in the highest final levels for people with longer than average sleep. Considering the suggested role of sleep for cognitive plasticity (Gorgoni et al., 2013; Walker & Stickgold, 2006), for older adults more sleep may in fact be better or at least not detrimental for learning (Richards et al., 2017). However, one should consider that participants in the current study slept shorter than recommended for optimal functioning (Hirshkowitz et al., 2015) and results may look different for more extreme long sleep durations. More improvements across the week for people with short average sleep durations could perhaps reflect effects of naps (Häusler et al., 2019; Sattari et al., 2019) or more potential for improvement because of a lower initial level of performance (Jaeggi et al., 2008). Sleep duration was not associated with performance variability, which partially aligns with previous results indicating that even under sleep deprivation older adults' performance variability may be relatively unimpaired (Adam et al., 2006).

Daily within-person variations in sleep duration were only relevant predictors of working memory performance for people sleeping short on average, suggesting relative resilience of older adults' cognitive performance to normal variations in daily sleep duration. Because this result differs from previous research in other age groups (e.g., Könen et al., 2016), it could be a consequence of focusing on older adults in this dissertation. Whereas one study found no evidence for age differences in associations between sleep duration and cognitive performance across the lifespan (Wild et al., 2018), sleep deprivation research has indicated that older compared to younger adults may need to recruit more cognitive resources to keep up performance following a night of sleep deprivation (Almklov et al., 2015; Drummond et al., 2005). Working on an interesting, challenging task in this study may have motivated the older adults to exert appropriate effort and thus compensate for the effects of short sleep up to a certain degree (Lim & Dinges, 2010). Furthermore, older adults' cognitive performance was observed to be relatively stable across several

weeks of repeated measurements (Schmiedek et al., 2013) during which normal variations in sleep would have occurred; this may also imply that older adults' cognitive performance is relatively immune to normal sleep variations.

In contrast to affective functioning and health perceptions, I only considered unidirectional effects of sleep on subsequent cognitive performance and not the other way round. This decision was based on theoretical considerations and previous research focusing on associations between sleep and subsequent cognitive functioning (e.g., Dzierzewski, 2012; Gamaldo et al., 2010; Könen et al., 2016). Nonetheless, one might ask whether it is possible that better cognitive performance could also predict better or longer sleep. There is some evidence that demanding cognitive training (before going to bed) may predict more continuous and better quality subsequent sleep (Cerasuolo et al., 2019; Conte et al., 2012). Similarly, cognitive training across eight weeks was associated with decreased times to fall asleep and more efficient sleep in older adults with insomnia; better performance on some of the trained cognitive tasks was associated with more sleep improvements (Haimov & Shatil, 2013). These results suggest that sleep may not only foster learning but that cognitive training could elicit changes in sleep, potentially to facilitate learning, although, as of yet, it is not clear which extent of training is necessary to exert such influence.

Furthermore, cognitive performance could be relevant as a moderator explaining effects of daily experiences on sleep, because better cognitive performance has been linked with more successful emotion regulation (Coifman et al., 2019; Garrison & Schmeichel, 2020; Pe et al., 2013). More successful emotion regulation may, in turn, be linked with better subsequent sleep (Babson, 2015; Espie, 2002). As such, cognitive performance would also be interesting to consider as a moderator for future research analyzing associations between daily functioning and subsequent sleep.

## **5.2 Age Effects Within Old Age**

Daily functioning differed with participant's age. With higher age, people experienced stronger NA (but not increased affective reactivity to stressors; Chapter 2). Similarly, old-old compared with young-old adults reported stronger pain and worse self-rated health (Chapter 3) and performed worse on the WM task (Chapter 4). These findings align with previous research, indicating decline across broad areas of functioning in very old age (P. B. Baltes & Smith, 2003).

However, participants' age was not associated with their sleep quality or sleep duration and the results showed no evidence for increased vulnerability to sleep loss in old age or vulnerability of sleep to daily functioning. Neither age (Chapter 2) nor age group (young-old compared with old-old adults; Chapter 3 and Chapter 4) consistently moderated links with sleep. The only age moderations occurred in links of both NA and stress with next night sleep quality (Chapter 3).

Additional analyses showed that the effect of age on links between NA and sleep quality disappeared when controlling for health and could thus be spurious. However, links between the number of stressors experienced and sleep quality also differed by age. For adults aged 60-63 years experiencing more stressors was linked with worse sleep; for adults aged 84 years and older more stress was unexpectedly linked with better sleep. The result suggesting that experiencing more stressors could be linked with better sleep quality may at first seem quite surprising. It is possible that experiencing more stressors could lead to exhaustion for old-old adults which could then be linked with better next night sleep (Grossi et al., 2015), but this suggestion is speculative and needs to be evaluated in future research.

Previous research has also disagreed on age-related vulnerabilities regarding sleep. Researchers have observed decreasing vulnerability of affective and cognitive functioning to sleep deprivation in older compared with younger adults (Adam et al., 2006; Duffy et al., 2009; Ready et al., 2009; Schwarz et al., 2019). Proposed explanations for these findings include better emotion regulation abilities (Charles & Luong, 2013; Ready et al., 2009) and a decreased need for sleep or lowered sleep propensity (Duffy et al., 2009) with older ages. However, empirical research has also found older adults' well-being to be more strongly impaired following sleep deprivation than that of younger adults (Birchler-Pedross et al., 2009). Similarly, normal variations in sleep were more strongly associated with affective well-being in older compared with middle-aged adults (Wrzus et al., 2014). Yet, none of these studies specifically assessed potential differences within old age. Furthermore, people generally differ in how much they are affected by insufficient sleep (Krizan & Hisler, 2021): It is possible that resistance vs. vulnerability to sleep loss in affective, cognitive, and physiological domains could be a relatively stable tendency (i.e., something like a trait) that is relatively independent from age.

Regarding the opposite direction, researchers have mainly suggested increasing vulnerability of sleep to external influences with older ages (Hot et al., 2015; Vgontzas et al., 2003). This could have several reasons. For example, with older ages, adults may experience difficulties in downregulating physiological arousal (Charles & Luong, 2013; Uchino et al., 2006) which could impact subsequent sleep. Furthermore, because circadian rhythms weaken with age, these weaker rhythms may be more easily disturbed (Hot et al., 2015; Vgontzas et al., 2003). Yet, in the studies contained in this dissertation, old-old adults' sleep was not more vulnerable to variations in daily functioning than young-old adults' sleep. It is possible that the relevant processes that might increase vulnerability occur earlier (i.e., from middle age to young-old age) which aligns with previous research finding changes in sleep architecture up until age 60 but not so much throughout old age (Ancoli-Israel et al., 2008).

Overall, the results from this dissertation speak against increasing vulnerability to normal

variations in sleep from young-old into old-old age. However, because of the relatively small number of old-old adults, statistical power to find moderating effects of age could have been reduced (Arend & Schäfer, 2019). Additionally, it should be kept in mind that the older adults who participated in the studies in this dissertation likely represent a high-functioning positive selection of the population, who, on average, experienced relatively little NA and pain and were in good health. As such, this dissertation should not be seen as evidence ruling out age effects in associations with sleep. It might instead encourage further research into both the personal and momentary conditions under which people may be more or less vulnerable to insufficient sleep.

### **5.3 Differential Roles of Self-Reported Sleep Quality and Sleep Duration in Daily Life**

To analyze the differential effects of sleep quality and sleep duration I repeated the analyses regarding sleep quality and affective functioning (Chapter 2) and regarding sleep duration and working memory (Chapter 4) with sleep duration and sleep quality respectively and additionally with both sleep measures included in the same model (for full results see Appendices A and B). New analyses were not necessary for links with health perceptions (Chapter 3) for which I already analyzed links with both sleep quality and sleep duration.

For associations between sleep and affective functioning (Chapter 2), the results were similar to those regarding sleep and health perceptions (Chapter 3): Sleep duration only predicted baseline NA when sleep quality was not part of the model (Tables A1 and A2), as was the case for self-rated health. For the opposite direction, none of the affective experiences predicted subsequent sleep duration (Tables A3 and A4). Given the regularly observed covariation between sleep duration and quality, these results suggest that observed links of sleep duration with certain aspects of functioning and well-being could be due to common links with sleep quality (e.g., Edwards et al., 2008; Sin et al., 2020). Overall, it seems that sleep quality may be more closely linked with domains of functioning associated with well-being (baseline NA and health perceptions) than sleep duration, which aligns with previous results regarding affective functioning and pain (Alsaadi et al., 2014; Konjarski et al., 2018; Whibley et al., 2019). However, there was relatively little variance in sleep duration and more extreme sleep durations could in fact be linked with worse mood, increased affective reactivity, or lowered health perceptions as indicated by research using sleep restriction or deprivation protocols (Krause et al., 2019; Minkel et al., 2012; Tomaso et al., 2021).

Furthermore, in the current analyses I only assessed linear but not quadratic (or other types of non-linear) associations with sleep duration; this means I did not consider that long sleep duration has also been associated with worse health (Jike et al., 2018) and may have detrimental effects on affective functioning and health perceptions (Liu et al., 2018; Magee et al., 2011; Wrzus et al., 2014). However, associations of longer sleep duration with worse self-rated health (Liu et al.,

2018; Magee et al., 2011) may be explained by worse objective health. Worse objective health could result in an increased sleep need and thus longer sleep (Jike et al., 2018; Wang et al., 2017). In this case, longer than usual sleep from day to day could be inconsequential for variations in self-rated health. Nonetheless, future research could consider testing for non-linear effects of sleep duration on affective functioning and self-rated health.

Regarding working memory performance (Chapter 4), sleep quality did not have a predictive effect on level, learning, variability (Tables B1 and B2), or daily variations (Tables B3 and B4). This result supports previous findings that daily sleep quality does not seem to be linked with cognitive functioning performance (Gamaldo et al., 2010; Holanda & Almondes, 2016; Zavec et al., 2020). One reason for this could be that older adults may be able to compensate for a night of bad sleep with increased effort (Frenda & Fenn, 2016). As indicated by previous research, sleep quality also does not align with more objectively measured sleep parameters, but it is possible that certain sleep parameters may be more important for cognitive function than self-reported sleep quality (Cavuoto et al., 2016; Ferrarelli et al., 2019).

Overall, daily variations in sleep quality thus seem more predictive for outcomes related to older adults' well-being than sleep duration, especially when both components are considered simultaneously. On the other hand, it is possible that sleep duration may become more important in the mid- to long-term – even for cognitive performance daily variations in sleep duration were only relevant when people were likely already sleep deprived, whereas sleep across one week was predictive for functioning.

#### **5.4 Strength, Limitations, and Future Directions**

In this dissertation, I used data from two highly similar ecological momentary assessment studies including older adults. Although the presented research has several strengths, I also want to acknowledge its limitations. As some of these strengths and limitations have already been discussed in Chapters 2-4, I mainly consider broader limitations and future directions here. One key strength of this dissertation is that it used EMA data collected across seven days in participants' usual environment as they went about their daily routines. EMA data implies relatively high ecological validity (Shiffman et al., 2008) and more realistic estimates of effect sizes, that is, of the strength and magnitude of the real-life links under study (e.g., compared with laboratory-based sleep deprivation studies). To make the best use of the collected EMA data, I applied state-of-the-art statistical methodology to assess within- and between-person associations. Concretely, I applied different multilevel structural equation models, including location-scale models (McNeish, 2020) and dynamic structural equation models (McNeish & Hamaker, 2019), to appropriately consider dependencies in the data resulting from repeated measurements and analyze the questions at hand.

In the next paragraphs I discuss strengths and limitations regarding the included samples, the applied assessment and measurement strategies, as well as important related topics not addressed in this dissertation.

#### **5.4.1 Sample**

As intended in the conceptualization of the EMIL and SOEP couple dynamics projects, including young-old and old-old adults and considering age effects is a great strength of this dissertation, because of a previous lack of research on links with sleep in these age groups. It is important to assess age effects within old age because of significant developmental changes occurring across potentially up to four decades (P. B. Baltes & Smith, 2003). However, this choice of sample also implies several limitations. For one, the results can, of course, not be generalized to younger age groups. Because of developmental changes in sleep architecture and affective functioning as well as declines in health and cognitive functioning (P. B. Baltes & Smith, 2003; Boulos et al., 2019; Kessler & Staudinger, 2009; Pinguart, 2001a; Salthouse, 2019) it is possible that the associations could differ between young adulthood, midlife, or old age. It would thus be desirable to apply a similar research protocol in different age groups across the lifespan.

Because of difficulties in recruiting old-old adults in particular, the samples considered in this dissertation are high functioning, relatively well educated, and likely represent a positive selection of the old-age populations. The positive selectivity also implies, that the results may not generalize to more vulnerable late life populations. Potentially, effects of sleep could even be stronger for more vulnerable people, but this topic requires further research. As previously discussed, because of the small number of old-old adults there might also have been limited power to detect age differences which should be amended by future research.

#### **5.4.2 Measurement and Assessment**

Further limitations are implied by the measurements employed in this dissertation, mainly the reliance on self-reports. First, relying on self-reports of sleep quality and sleep duration might suffer from certain blind spots. For example, people can both over- and underestimate their total sleep time and there is little overlap between subjective and objective measurements of sleep quality (Boulos et al., 2019; Girschik et al., 2012; Kaplan et al., 2017). Despite more consistent links of self-reported sleep with affective functioning and health perceptions (Konjarski et al., 2018; O'Brien et al., 2011), it would thus be interesting to identify more objective sleep measures linked with daily functioning in old age. Particularly, combining self-reports and actigraphy might help disentangle the mechanisms underlying differential effects of sleep quality and sleep duration. Furthermore, previous research has indicated potential effects of self-rated health on sleep-onset

latency and sleep efficiency (Simoes Maria et al., 2020) which would be promising to assess with regard to affective reactivity as well. Second, because NA, stress, pain, and self-rated health were equally self-reported, the observed links could be overestimated. In addition to applying objective measures of sleep, such as actigraphy, one could consider analyzing more objective measurements of daily functioning such as heart rate variability or cortisol as indicators for affective reactivity (Kudielka et al., 2012; J. Yang & Kershaw, 2022).

Cognitive performance was already objectively assessed as participants repeatedly performed a working memory updating task. Generally, average performance in repeated cognitive assessments in daily life studies is highly correlated with more traditional cognitive tests (Sliwinski et al., 2018). Yet, repeated performance across time and situations can even be considered more representative of everyday cognitive functioning than traditional one-off cognitive tests in a controlled laboratory environment. Averaging across repeated assessments can “cancel out” effects of varying momentary states, such as tiredness, mood, or stress, that are also present (but generally not controlled) in one-off lab assessments (Sliwinski et al., 2018). The effects of such momentary states can also be studied. Additionally, momentary assessments of cognitive performance allow considering aspects other than mean performance, such as retest learning and short-term variability, which is not yet often done. Despite these strengths, the limited number of only two trials per assessment could be considered as a limitation as it did not allow assessment of variability on a shorter timescale (i.e., trial-to-trial within the same assessment). Furthermore, the employed task only had one level of difficulty, but effects of sleep could differ across difficulties (Gerhardsson et al., 2019; Terán-Pérez et al., 2012). Although WM updating is an important function theoretically linked with sleep, other cognitive functions could be differentially associated with sleep (Kusztor et al., 2019; Santisteban et al., 2019) and may be considered in future research.

In addition to issues of measurement, further limitations are associated with the assessment schedule used. First, using fixed (compared with, e.g., semi-random intervals) means participants could anticipate coming assessments and potentially structure their activities around the assessments which may have reduced ecological validity. Second, the studies included in this dissertation covered only 7 days and six daily assessments. Because of this restriction, some estimates (such as daily affective reactivity and person-specific estimates of sleep effects) might profit from longer time-series and more assessments to be assessed more reliably (Neubauer et al., 2020). However, in both depth of measurement and assessment frequency, one needs to weigh participant burden against desires for more comprehensive measurements. As such, future research could opt for different approaches, depending on the main question at hand: longer time-series (i.e., more days) could help to more reliably predict broad effects of sleep on daily functioning or vice versa. On the other hand, more intense (i.e., more frequent) momentary assessment schedules

would allow assessing dynamic aspects of affective reactivity, short-term variations in cognitive functioning, or short-term interactions between different functions in more detail. Lastly, more comprehensive measurements, for example including more information on the appraisal of situations, stressors, and pain, or using actigraphy to measure sleep could zoom into the mechanisms at play for the effects found in this dissertation.

### **5.4.3 Topics in Need of Future Research**

Finally, despite the necessarily restricted scope of any dissertation, I address a few limitations in terms of topics that were not covered. In this dissertation, I focused on night-time sleep, but as an important limitation it was not recorded whether participants took naps during the day. Some research has included naps by considering total sleep time within 24h (e.g., Devore et al., 2014), but many others have not assessed or reported on them either (e.g., Abeler et al., 2021; Gamaldo et al., 2010; McCrae et al., 2008; Sin et al., 2021). However, naps can increase daily functioning but could also have detrimental effects, depending on length and timing (for a review, see Z. Zhang et al., 2020). Naps should thus be considered in future research assessing links between sleep and daily functioning.

In the domain of affective functioning, I used affective reactivity as a proxy for emotion regulation, which was an important first step but does of course not address many other aspects of emotion regulation (e.g., Gross, 1998). Gross' (1998) process model of emotion regulation includes actions, such as situation selection, attention, and appraisal in addition to responses. For example, one strength of older adults' emotion regulation is avoiding potentially stressful situations (Charles & Luong, 2013), which they may also choose to do after nights with worse sleep. To find out whether sleep may be differentially associated with different components of the emotion regulation process, more detailed assessments of emotion regulation processes should be considered.

Furthermore, I focused on NA but research has also implied a potential role of positive affect (PA) in associations with sleep and other domains of functioning. Not only did worse sleep predict lower PA in some previous research (Konjarski et al., 2018), but shorter sleep duration actually predicted affective reactivity in PA as well, that is stronger decreases in positive affect following stressors (Sin et al., 2017). Additionally, PA has been identified as a potential buffer limiting the effects of low sleep quality on stress reactivity (Blaxton et al., 2017). For the opposite direction, PA might be linked to more successful emotion regulation and better coping (Fredrickson, 2004) and could thus buffer negative effects of affective reactivity, pain, or low self-rated health, thereby protecting sleep (A. D. Ong et al., 2013; Strand et al., 2006). Similarly, stronger PA may predict better cognitive performance (Brose et al., 2014). Accordingly, PA could be considered as both an interesting outcome in and of itself or as a potential moderator in associations between sleep and



daily functioning.

As a strength of this dissertation, I included several central domains of psychological functioning that have also been considered to be important for successful aging: affective functioning, aspects of both health and physical function, as well as cognitive function (Fernández-Ballesteros, 2019; Urtamo et al., 2019). However, future research could include more objective measures of health and address active engagement and social functioning as well. Linking these domains with sleep would then enable researchers to better identify how relevant sleep is to different domains of functioning in old age.

## **5.5 Practical Implications**

In addition to the suggestions for future research made in the previous section, I would like to address some implications of the results from this dissertation. I focus on two main topics: First, the potential relevance of short-term links for long-term developments (which might provide insights to improve developmental trajectories in old age) and, second, the potential of interventions to improve older adults' sleep and daily lives.

### **5.5.1 *Could Short-Term Links Be Important for Long-Term Developments?***

Sleep in midlife and changes in sleep across longer periods of time have been suggested to meaningfully impact aging (Driscoll et al., 2008; E. E. Lee, 2019). In line with the short-term associations found in this dissertation and elsewhere, research also reports long-term links of insufficient sleep with decreasing mental and physical health and cognitive function (J. A. Lee et al., 2016; Spira et al., 2014; Sun et al., 2018; Wennberg et al., 2017).

Overall, the results from this dissertation indicated small effects of daily variations in sleep on daily functioning and vice versa, but this is not surprising. Psychological phenomena in daily life are determined by multiple factors, necessarily making small single influences the norm. At the same time, this does not mean these small effects are irrelevant. On the contrary, daily effects, by means of their frequent repetition, could be the basis for important long-term consequences. Therefore, insights into the daily interplay between sleep and functioning may reveal potential pathways to improve long-term aging trajectories.

Supporting this suggestion, emotional vulnerability to short sleep (i.e., stronger increase in NA following short sleep) predicted chronic medical conditions eight years later (Sin et al., 2021). The authors suggest potential psychosocial and behavioral pathways that may underlie this association: For example, people who are vulnerable to effects of sleep loss may exhibit poorer emotion regulation, show poorer health behaviors, and reduce their social or work activities. The effects of these behavioral consequences may then accumulate and increase the risk for chronic

health conditions (Sin et al., 2021). Similar effects of short-term associations have been observed for long-term effects of affective reactivity and recovery on health outcomes several years later (Leger et al., 2018; Piazza et al., 2013). Potential mechanisms include repeated and prolonged activation of the HPA axis and the cardiovascular system as well as elevated inflammation that accompany affective reactivity (Leger et al., 2018; Sin et al., 2015). Transferring this back to sleep, acute physiologic effects of sleeping insufficiently that may also be associated with affective functioning and health perceptions (e.g., HPA axis activity and inflammation) could over time lead to chronic dysregulation and subsequently negatively impact health (Haack et al., 2020). One avenue to start formally assessing the long-term relevance of short-term associations with sleep for preserved functioning in late adulthood would be longitudinal measurement burst studies scrutinizing both the stability of short-term associations of sleep with different areas of functioning and whether these short-term associations predict long-term developments. If short-term associations turn out to be the basis for long-term developments, vulnerability to insufficient sleep would be one important factor to consider for maintaining good psychological and physical functioning in late life. In line with this, I think it will be crucial for future research to assess who is more or less vulnerable to effects of sleep and whose sleep is vulnerable to daily experiences, for example to identify people who could profit from interventions.

### **5.5.2 *Could Sleep Interventions Improve Older Adults' Daily Lives?***

The results from this dissertation may also be useful to inform the development of interventions to improve older adults' well-being and functioning. The results suggest that sleep is an important predictor of daily functioning and interventions aiming to improve sleep could thus have downstream effects on functioning in daily life. Research already showed that, in addition to improving sleep, sleep interventions ameliorated pain (Koffel et al., 2019) and improved mental health in the long-term (A. J. Scott et al., 2021). Similarly, the observed association of affective reactivity with sleep quality suggests that interventions targeting emotion regulation could potentially improve sleep quality, e.g., through mindfulness practice. The effect of emotion regulation and mindfulness on sleep is supported by research showing that an experiential emotion regulation approach, encompassing the mindful, non-evaluative experience of emotions, improved sleep efficiency and duration compared with a cognitive-analytical emotion regulation approach (Vandekerckhove et al., 2012). Because of bidirectional links found between sleep quality and self-rated health, both improving sleep and factors associated with self-rated health could lead to a potentially self-enhancing cycle (Arnison et al., 2022; Fank et al., 2022; Gothe et al., 2020; Parra-Rizo & Sanchís-Soler, 2021).

One classic approach to improve sleep is cognitive behavioral therapy for insomnia (CBT-I)

– as implied in the name this intervention was developed to treat insomnia. However, CBT-I may also be useful to improve sleep for people who do not fulfill the criteria for an insomnia diagnosis (Denis et al., 2020). CBT-I focuses on identifying clients' personal sleep habits and factors perpetuating sleep problems and teaches clients skills, including sleep hygiene, sleep restriction, relaxation techniques, and reappraising dysfunctional thoughts regarding sleep (Bennett, 2020). Following a six-week digital CBT-I protocol, people who did not fulfill the criteria for an insomnia diagnosis, experienced a reduction in sleep problems as well as reductions in anxiety and life stress (Denis et al., 2020).

In addition to the classical cognitive-behavioral approach, different types of interventions have successfully improved subjective sleep quality in old age. A meta-analysis focusing on healthy older adults concluded that interventions centering physical activity and interventions centering psychological processes (e.g., mindfulness, psychoeducation) are generally effective in improving self-reported sleep quality for older adults with and without sleep disorders (Sella et al., 2022). Similarly, an umbrella review which differently categorized types of interventions found mind-body-exercise was particularly useful in old age; mind-body exercise combines physical exercise with meditative components and includes activities like yoga, tai chi, and qigong (Albakri et al., 2021). A review focusing on mindfulness interventions similarly concluded that mindfulness seems beneficial for self-reported sleep outcomes but the effects on objective sleep parameters were less clear (J. C. Ong & Moore, 2020).

Some of these interventions have not only been linked with sleep but could also impact daily functioning more directly. For example, mindfulness practice can enhance emotion regulation and has been linked with reduced cognitive-emotional arousal (J. C. Ong et al., 2018). The potential effectiveness of mindfulness is also supported by a naturalistic study showing that increased state mindfulness buffered the link between sleep and pain (Mu & Lee, 2022). Both mindfulness practice and physical activity may further be linked with maintained cognitive function in old age (Hamer et al., 2018; Kurth et al., 2017). Physical activity could additionally reduce negative consequences of pain (Gyasi et al., 2022) and likely has an additional positive effect on more objective health parameters, such as resting heart rate and heart rate variability (Buchheit et al., 2004). Whether physical activity positively predicts self-rated health or vice versa has remained unclear and warrants further research (Kekäläinen et al., 2020; Parra-Rizo & Sanchís-Soler, 2021).

Overall, based on the results from this dissertation and previous research, it would seem promising to develop and test the effects of interventions including mindfulness, physical activity, and/or cognitive-behavioral strategies on sleep and daily functioning. Ideally, one could hope that short-term improvements gained through interventions may extend to improved long-term functioning and more successful aging.

## 5.6 Conclusion

Sleep may be crucial to several important functions in older adults' daily lives. Sleep is a relevant predictor for older adults' daily well-being and functioning and should be routinely addressed when practitioners interact with older adults for affective, health-related, or cognitive complaints. The results from my dissertation suggest that sleeping long enough may be relevant for older adults' short-term cognitive performance and plasticity. Sleeping well, on the other hand, seemed more important for older adults' well-being, including affective and physical functioning. The successful regulation of stress and better self-rated health predicted better, but not longer sleep. The results stress the importance to distinguish between sleep quality and sleep duration. In the future, interventions, maybe including physical activity, mindfulness and/or cognitive-behavioral strategies, could potentially improve older adults' sleep and daily functioning and might thereby support favorable developmental trajectories and successful aging.

## References

- Abeler, K., Bergvik, S., Sand, T., & Friberg, O. (2021). Daily associations between sleep and pain in patients with chronic musculoskeletal pain. *Journal of Sleep Research, 30*(4), e13237. <https://doi.org/10.1111/jsr.13237>
- Adam, M., Rétey, J. V., Khatami, R., & Landolt, H.-P. (2006). Age-related changes in the time course of vigilant attention during 40 hours without sleep in men. *Sleep, 29*(1), 55–57. <https://doi.org/10.1093/sleep/29.1.55>
- Affleck, G., Urrows, S., Tennen, H., Higgins, P., & Abeles, M. (1996). Sequential daily relations of sleep, pain intensity, and attention to pain among women with fibromyalgia. *Pain, 68*(2), 363–368. [https://doi.org/10.1016/S0304-3959\(96\)03226-5](https://doi.org/10.1016/S0304-3959(96)03226-5)
- Afolalu, E. F., Ramlee, F., & Tang, N. K. Y. (2018). Effects of sleep changes on pain-related health outcomes in the general population: A systematic review of longitudinal studies with exploratory meta-analysis. *Sleep Medicine Reviews, 39*, 82–97. <https://doi.org/10.1016/j.smr.2017.08.001>
- Åkerstedt, T., Axelsson, J., Lekander, M., Orsini, N., & Kecklund, G. (2013). The daily variation in sleepiness and its relation to the preceding sleep episode--a prospective study across 42 days of normal living. *Journal of Sleep Research, 22*(3), 258–265. <https://doi.org/10.1111/jsr.12014>
- Åkerstedt, T., Hume, K., Minors, D., & Waterhouse, J. (1994). The subjective meaning of good sleep, an intraindividual approach using the Karolinska Sleep Diary. *Perceptual and Motor Skills, 79*(1 Pt 1), 287–296. <https://doi.org/10.2466/pms.1994.79.1.287>
- Åkerstedt, T., Kecklund, G., & Axelsson, J. (2007). Impaired sleep after bedtime stress and worries. *Biological Psychology, 76*(3), 170–173. <https://doi.org/10.1016/j.biopsycho.2007.07.010>
- Åkerstedt, T., Nilsson, P. M., & Kecklund, G. (2009). Sleep and recovery. In S. Sonnentag, P. L. Perrewé, & D. C. Ganster (Eds.), *Research in Occupational Stress and Well-being. Current perspectives on job-stress recovery* (Vol. 7, pp. 205–247). Emerald Group Publishing Limited. [https://doi.org/10.1108/S1479-3555\(2009\)0000007009](https://doi.org/10.1108/S1479-3555(2009)0000007009)
- Åkerstedt, T., Orsini, N., Petersen, H., Axelsson, J., Lekander, M., & Kecklund, G. (2012). Predicting sleep quality from stress and prior sleep--a study of day-to-day covariation across six weeks. *Sleep Medicine, 13*(6), 674–679. <https://doi.org/10.1016/j.sleep.2011.12.013>
- Albakri, U., Drotos, E., & Meertens, R. (2021). Sleep health promotion interventions and their effectiveness: An umbrella review. *International Journal of Environmental Research and Public Health, 18*(11). <https://doi.org/10.3390/ijerph18115533>

- Allaire, J. C., & Marsiske, M. (2005). Intraindividual variability may not always indicate vulnerability in elders' cognitive performance. *Psychology and Aging, 20*(3), 390–401. <https://doi.org/10.1037/0882-7974.20.3.390>
- Almklov, E. L., Drummond, S. P. A., Orff, H., & Alhassoon, O. M. (2015). The effects of sleep deprivation on brain functioning in older adults. *Behavioral Sleep Medicine, 13*(4), 324–345. <https://doi.org/10.1080/15402002.2014.905474>
- Alsaadi, S. M., McAuley, J. H., Hush, J. M., Lo, S., Bartlett, D. J., Grunstein, R. R., & Maher, C. G. (2014). The bidirectional relationship between pain intensity and sleep disturbance/quality in patients with low back pain. *The Clinical Journal of Pain, 30*(9), 755–765. <https://doi.org/10.1097/AJP.0000000000000055>
- American Psychological Association. (n.d.). Sleep. In *APA Dictionary of Psychology*. <https://dictionary.apa.org/sleep>
- Ancoli-Israel, S., Ayalon, L., & Salzman, C. (2008). Sleep in the elderly: Normal variations and common sleep disorders: Normal Variations and Common Sleep Disorders. *Harvard Review of Psychiatry, 16*(5), 279–286. <https://doi.org/10.1080/10673220802432210>
- Arend, M. G., & Schäfer, T. (2019). Statistical power in two-level models: A tutorial based on Monte Carlo simulation. *Psychological Methods, 24*(1), 1–19. <https://doi.org/10.1037/met0000195>
- Arnison, T., Schrooten, M. G. S., Bauducco, S., Jansson-Fröjmark, M., & Persson, J. (2022). Sleep phase and pre-sleep arousal predicted co-developmental trajectories of pain and insomnia within adolescence. *Scientific Reports, 12*(1), 4480. <https://doi.org/10.1038/s41598-022-08207-y>
- Asparouhov, T., & Muthén, B. (2010). *Bayesian analysis using Mplus: Technical implementation (3rd ed.)*. Muthén & Muthén. <https://www.statmodel.com/download/Bayes3.pdf>
- Babson, K. A. (2015). The interrelations between sleep and fear/anxiety: Implications for behavioural treatment. In K. A. Babson & M. T. Feldner (Eds.), *Sleep and affect: Assessment, theory, and clinical implications* (pp. 143–162). Academic Press. <https://doi.org/10.1016/B978-0-12-417188-6.00007-4>
- Babson, K. A., & Feldner, M. T. (2015). Sleep and affect: An integrative synthesis and future directions. In K. A. Babson & M. T. Feldner (Eds.), *Sleep and affect: Assessment, theory, and clinical implications* (pp. 463–483). Academic Press. <https://doi.org/10.1016/B978-0-12-417188-6.00021-9>
- Baddeley, A. (1992). Working memory. *Science, 255*(5044), 556–559. <https://doi.org/10.1126/science.1736359>

- Bademli, K., Lok, N., Canbaz, M., & Lok, S. (2019). Effects of Physical Activity Program on cognitive function and sleep quality in elderly with mild cognitive impairment: A randomized controlled trial. *Perspectives in Psychiatric Care*, 55(3), 401–408. <https://doi.org/10.1111/ppc.12324>
- Baglioni, C., Battagliese, G., Feige, B., Spiegelhalder, K., Nissen, C., Voderholzer, U., Lombardo, C., & Riemann, D. (2011). Insomnia as a predictor of depression: A meta-analytic evaluation of longitudinal epidemiological studies. *Journal of Affective Disorders*, 135(1-3), 10–19. <https://doi.org/10.1016/j.jad.2011.01.011>
- Baltes, M. M. (1998). The psychology of the oldest-old: the fourth age. *Current Opinion in Psychiatry*, 11(4), 411–415.
- Baltes, P. B., & Smith, J. (2003). New frontiers in the future of aging: From successful aging of the young old to the dilemmas of the fourth age. *Gerontology*, 49(2), 123–135. <https://doi.org/10.1159/000067946>
- Barry, L. E., O'Neill, S., Heaney, L. G., & O'Neill, C. (2021). Stress-related health depreciation: Using allostatic load to predict self-rated health. *Social Science & Medicine* (1982), 283, 114170. <https://doi.org/10.1016/j.socscimed.2021.114170>
- Bastien, C. (2001). Validation of the Insomnia Severity Index as an outcome measure for insomnia research. *Sleep Medicine*, 2(4), 297–307. [https://doi.org/10.1016/S1389-9457\(00\)00065-4](https://doi.org/10.1016/S1389-9457(00)00065-4)
- Batterham, P. J., Bunce, D., Mackinnon, A. J., & Christensen, H. (2014). Intra-individual reaction time variability and all-cause mortality over 17 years: A community-based cohort study. *Age and Ageing*, 43(1), 84–90. <https://doi.org/10.1093/ageing/aft116>
- Bennett, D. (2020). Cognitive-Behavioral Therapy for Insomnia (CBT-I). In Sedky & Lonuzzi (Eds.), *Sleep Medicine and Mental Health* (pp. 47–66). Springer International Publishing. [https://doi.org/10.1007/978-3-030-44447-1\\_3](https://doi.org/10.1007/978-3-030-44447-1_3)
- Bin, Y. S. (2016). Is sleep quality more important than sleep duration for public health? *Sleep*, 39(9), 1629–1630. <https://doi.org/10.5665/sleep.6078>
- Birchler-Pedross, A., Schröder, C. M., Münch, M., Knoblauch, V., Blatter, K., Schnitzler-Sack, C., Wirz-Justice, A., & Cajochen, C. (2009). Subjective well-being is modulated by circadian phase, sleep pressure, age, and gender. *Journal of Biological Rhythms*, 24(3), 232–242. <https://doi.org/10.1177/0748730409335546>
- Blågestad, T., Pallesen, S., Lunde, L.-H., Sivertsen, B., Nordhus, I.-H., & Grønli, J. (2012). Sleep in older chronic pain patients: A comparative polysomnographic study. *The Clinical Journal of Pain*, 28(4), 277–283. <https://doi.org/10.1097/AJP.0b013e3182313899>

- Blaxton, J. M., Bergeman, C. S., Whitehead, B. R., Braun, M. E., & Payne, J. D. (2017). Relationships among nightly sleep quality, daily stress, and daily affect. *The Journals of Gerontology: Series B*, *72*(3), 363–372. <https://doi.org/10.1093/geronb/gbv060>
- Boccabella, A., & Malouf, J. (2017). How do sleep-related health problems affect functional status according to sex? *Journal of Clinical Sleep Medicine*, *13*(5), 685–692. <https://doi.org/10.5664/jcsm.6584>
- Bolger, N., & Schilling, E. A. (1991). Personality and the problems of everyday life: The role of neuroticism in exposure and reactivity to daily stressors. *Journal of Personality*, *59*(3), 355–386. <https://doi.org/10.1111/j.1467-6494.1991.tb00253.x>
- Boulos, M. I., Jairam, T., Kendzerska, T., Im, J., Mekhael, A., & Murray, B. J. (2019). Normal polysomnography parameters in healthy adults: a systematic review and meta-analysis. *The Lancet Respiratory Medicine*, *7*(6), 533–543. [https://doi.org/10.1016/S2213-2600\(19\)30057-8](https://doi.org/10.1016/S2213-2600(19)30057-8)
- Bouwman, M. E. J., Bos, E. H., Hoenders, H. J. R., Oldehinkel, A. J., & Jonge, P. de (2017). Sleep quality predicts positive and negative affect but not vice versa. An electronic diary study in depressed and healthy individuals. *Journal of Affective Disorders*, *207*, 260–267. <https://doi.org/10.1016/j.jad.2016.09.046>
- Brose, A., Lövdén, M., & Schmiedek, F. (2014). Daily fluctuations in positive affect positively covary with working memory performance. *Emotion*, *14*(1), 1–6. <https://doi.org/10.1037/a0035210>
- Brose, A., Schmiedek, F., Gerstorf, D., & Voelkle, M. C. (2020). The measurement of within-person affect variation. *Emotion*, *20*(4), 677–699. <https://doi.org/10.1037/emo0000583>
- Brose, A., Schmiedek, F., Lövdén, M., & Lindenberger, U. (2012). Daily variability in working memory is coupled with negative affect:: The role of attention and motivation. *Emotion*, *12*(3), 605–617. <https://doi.org/10.1037/a0024436>
- Buchheit, M., Simon, C., Viola, A. U., Doutreleau, S., Piquard, F., & Brandenberger, G. (2004). Heart rate variability in sportive elderly: Relationship with daily physical activity. *Medicine and Science in Sports and Exercise*, *36*(4), 601–605. <https://doi.org/10.1249/01.mss.0000121956.76237.b5>
- Burke, K. E., Schnittger, R., O'Dea, B., Buckley, V., Wherton, J. P., & Lawlor, B. A. (2012). Factors associated with perceived health in older adult Irish population. *Aging & Mental Health*, *16*(3), 288–295. <https://doi.org/10.1080/13607863.2011.628976>
- Buysse, D. J., Reynolds, C. F., Monk, T. H., Berman, S. R., & Kupfer, D. J. (1989). The Pittsburgh sleep quality index: A new instrument for psychiatric practice and research. *Psychiatry Research*, *28*(2), 193–213. [https://doi.org/10.1016/0165-1781\(89\)90047-4](https://doi.org/10.1016/0165-1781(89)90047-4)



- Buysse, D. J., Reynolds III, C. F., Monk, T. H., Hoch, C. C., Yeager, A. L., & Kupfer, D. J. (1991). Quantification of subjective sleep quality in healthy elderly men and women using the Pittsburgh Sleep Quality Index (PSQI). *Sleep*, *14*(4), 331–338.  
<https://doi.org/10.1093/sleep/14.4.331>
- Byun, J.-H., Kim, K. T., Moon, H.-J., Motamedi, G. K., & Cho, Y. W. (2019). The first night effect during polysomnography, and patients' estimates of sleep quality. *Psychiatry Research*, *274*, 27–29. <https://doi.org/10.1016/j.psychres.2019.02.011>
- Carney, C. E., Buysse, D. J., Ancoli-Israel, S., Edinger, J. D., Krystal, A. D., Lichstein, K. L., & Morin, C. M. (2012). The consensus sleep diary: Standardizing prospective sleep self-monitoring. *Sleep*, *35*(2), 287–302. <https://doi.org/10.5665/sleep.1642>
- Carney, C. E., Harris, A. L., Moss, T. G., & Edinger, J. D. (2010). Distinguishing rumination from worry in clinical insomnia. *Behaviour Research and Therapy*, *48*(6), 540–546.  
<https://doi.org/10.1016/j.brat.2010.03.004>
- Casement, M. D., Broussard, J. L., Mullington, J. M., & Press, D. Z. (2006). The contribution of sleep to improvements in working memory scanning speed: A study of prolonged sleep restriction. *Biological Psychology*, *72*(2), 208–212.  
<https://doi.org/10.1016/j.biopsycho.2005.11.002>
- Cavuoto, M. G., Ong, B., Pike, K. E., Nicholas, C. L., Bei, B., & Kinsella, G. J. (2016). Objective but not subjective sleep predicts memory in community-dwelling older adults. *Journal of Sleep Research*, *25*(4), 475–485. <https://doi.org/10.1111/jsr.12391>
- Cerasuolo, M., Conte, F., Cellini, N., Fusco, G., Giganti, F., Malloggi, S., & Ficca, G. (2019). The effect of complex cognitive training on subsequent night sleep. *Journal of Sleep Research*, e12929. <https://doi.org/10.1111/jsr.12929>
- Chaput, J.-P., McNeil, J., Després, J.-P., Bouchard, C., & Tremblay, A. (2013). Short sleep duration as a risk factor for the development of the metabolic syndrome in adults. *Preventive Medicine*, *57*(6), 872–877. <https://doi.org/10.1016/j.ypmed.2013.09.022>
- Charles, S. T. (2010). Strength and vulnerability integration: A model of emotional well-being across adulthood: A model of emotional well-being across adulthood. *Psychological Bulletin*, *136*(6), 1068–1091. <https://doi.org/10.1037/a0021232>
- Charles, S. T., & Luong, G. (2013). Emotional experience across adulthood. *Current Directions in Psychological Science*, *22*(6), 443–448. <https://doi.org/10.1177/0963721413497013>
- Charles, S. T., Piazza, J. R., Mogle, J., Sliwinski, M. J., & Almeida, D. M. (2013). The wear and tear of daily stressors on mental health. *Psychological Science*, *24*(5), 733–741.  
<https://doi.org/10.1177/0956797612462222>

- Charlson, M. E., Pompei, P., Ales, K. L., & MacKenzie, C. (1987). A new method of classifying prognostic comorbidity in longitudinal studies: Development and validation. *Journal of Chronic Diseases*, 40(5), 373–383. [https://doi.org/10.1016/0021-9681\(87\)90171-8](https://doi.org/10.1016/0021-9681(87)90171-8)
- Chattu, V. K., Manzar, M. D., Kumary, S., Burman, D., Spence, D. W., & Pandi-Perumal, S. R. (2018). The global problem of insufficient sleep and its serious public health implications. *Healthcare*, 7(1), 1–16. <https://doi.org/10.3390/healthcare7010001>
- Chaudhary, M., & Selvamani, Y. (2021). Association between back pain and subjective health, wellbeing and sleep problems among older adults in six middle-income countries: a cross-sectional study. *Journal of Public Health*, 1–10. <https://doi.org/10.1007/s10389-020-01474-x>
- Christian, L. M., Glaser, R., Porter, K., Malarkey, W. B., Beversdorf, D., & Kiecolt-Glaser, J. K. (2011). Poorer self-rated health is associated with elevated inflammatory markers among older adults. *Psychoneuroendocrinology*, 36(10), 1495–1504. <https://doi.org/10.1016/j.psyneuen.2011.04.003>
- Chui, H., Hoppmann, C. A., Gerstorf, D., Walker, R., & Luszcz, M. A. (2014). Cumulative load of depressive symptoms is associated with cortisol awakening response in very old age. *Research in Human Development*, 11(2), 126–141. <https://doi.org/10.1080/15427609.2014.906738>
- Coifman, K. G., Kane, M. J., Bishop, M., Matt, L. M., Nylocks, K. M., & Aurora, P. (2019). Predicting negative affect variability and spontaneous emotion regulation: Can working memory span tasks estimate emotion regulatory capacity? *Emotion*. Advance online publication. <https://doi.org/10.1037/emo0000585>
- Conte, F., Carobbi, G., Errico, B. M., & Ficca, G. (2012). The effects of pre-sleep learning on sleep continuity, stability, and organization in elderly individuals. *Frontiers in Neurology*, 3, 109. <https://doi.org/10.3389/fneur.2012.00109>
- Conway, A. R. A., Kane, M. J., & Engle, R. W. (2003). Working memory capacity and its relation to general intelligence. *Trends in Cognitive Sciences*, 7(12), 547–552. <https://doi.org/10.1016/j.tics.2003.10.005>
- Cox, S. R., Ritchie, S. J., Allerhand, M., Hagenaars, S. P., Radakovic, R., Breen, D. P., Davies, G., Riha, R. L., Harris, S. E., Starr, J. M., & Deary, I. J. (2019). Sleep and cognitive aging in the eighth decade of life. *Sleep*, 42(4), zsz019. <https://doi.org/10.1093/sleep/zsz019>
- Dahlgren, A., Kecklund, G., Theorell, T., & Åkerstedt, T. (2009). Day-to-day variation in saliva cortisol--relation with sleep, stress and self-rated health. *Biological Psychology*, 82(2), 149–155. <https://doi.org/10.1016/j.biopsycho.2009.07.001>

- Daniëls, N. E. M., Bartels, S. L., Verhagen, S. J. W., van Knippenberg, R. J. M., Vugt, M. E. de, & Delespaul, P. A. E. G. (2020). Digital assessment of working memory and processing speed in everyday life: Feasibility, validation, and lessons-learned. *Internet Interventions, 19*, 100300. <https://doi.org/10.1016/j.invent.2019.100300>
- Davin, S., Wilt, J., Covington, E., & Scheman, J. (2014). Variability in the relationship between sleep and pain in patients undergoing interdisciplinary rehabilitation for chronic pain. *Pain Medicine, 15*(6), 1043–1051. <https://doi.org/10.1111/pme.12438>
- Denis, D., Eley, T. C., Rijdsdijk, F., Zavos, H. M. S., Keers, R., Espie, C. A., Luik, A. I., Badini, I., Derveeuw, S., Hodson, J., & Gregory, A. M. (2020). Is digital cognitive behavioural therapy for insomnia effective in treating sub-threshold insomnia: A pilot RCT. *Sleep Medicine, 66*, 174–183. <https://doi.org/10.1016/j.sleep.2019.10.007>
- Devore, E. E., Grodstein, F., Duffy, J. F., Stampfer, M. J., Czeisler, C. A., & Schernhammer, E. S. (2014). Sleep duration in midlife and later life in relation to cognition. *Journal of the American Geriatrics Society, 62*(6), 1073–1081. <https://doi.org/10.1111/jgs.12790>
- Devore, E. E., Grodstein, F., & Schernhammer, E. S. (2016). Sleep duration in relation to cognitive function among older adults: A systematic review of observational studies. *Neuroepidemiology, 46*(1), 57–78. <https://doi.org/10.1159/000442418>
- Diamond, A. (2013). Executive functions. *Annual Review of Psychology, 64*, 135–168. <https://doi.org/10.1146/annurev-psych-113011-143750>
- Dirk, J., & Schmiedek, F. (2016). Fluctuations in elementary school children's working memory performance in the school context. *Journal of Educational Psychology, 108*(5), 722–739. <https://doi.org/10.1037/edu0000076>
- Doran, S. M., van Dongen, H. P. A., & Dinges, D. F. (2001). Sustained attention performance during sleep deprivation: evidence of state instability. *Archives Italiennes De Biologie, 139*, 253–267.
- Driscoll, H. C., Serody, L., Patrick, S., Maurer, J., Bensasi, S., Houck, P. R., Mazumdar, S., Nofzinger, E. A., Bell, B., Nebes, R. D., Miller, M. D., & Reynolds, C. F. (2008). Sleeping well, aging well: A descriptive and cross-sectional study of sleep in "successful agers" 75 and older. *The American Journal of Geriatric Psychiatry, 16*(1), 74–82. <https://doi.org/10.1097/JGP.0b013e3181557b69>
- Drummond, S. P. A., Meloy, M. J., Yanagi, M. A., Orff, H. J., & Brown, G. G. (2005). Compensatory recruitment after sleep deprivation and the relationship with performance. *Psychiatry Research, 140*(3), 211–223. <https://doi.org/10.1016/j.psychresns.2005.06.007>

- Duffy, J. F., Willson, H. J., Wang, W., & Czeisler, C. A. (2009). Healthy older adults better tolerate sleep deprivation than young adults. *Journal of the American Geriatrics Society*, *57*(7), 1245–1251. <https://doi.org/10.1111/j.1532-5415.2009.02303.x>
- Dzierzewski, J. M. (2012). *Cognitive change in older adults: practice effects, short-term variability, and their association with sleep*. University of Florida. Doctoral Dissertation.
- Dzierzewski, J. M., Marsiske, M., Morgan, A. A., Buman, M. P., Giacobbi, P. R., Roberts, B., & McCrae, C. S. (2013). Cognitive inconsistency and practice-related learning in older adults. *GeroPsych*, *26*(3), 173–184. <https://doi.org/10.1024/1662-9647/a000096>
- Edmonds, E. C., Delano-Wood, L., Galasko, D. R., Salmon, D. P., & Bondi, M. W. (2014). Subjective cognitive complaints contribute to misdiagnosis of mild cognitive impairment. *Journal of the International Neuropsychological Society*, *20*(8), 836–847. <https://doi.org/10.1017/S135561771400068X>
- Edwards, R. R., Almeida, D. M., Klick, B., Haythornthwaite, J. A., & Smith, M. T [Michael T.] (2008). Duration of sleep contributes to next-day pain report in the general population. *Pain*, *137*(1), 202–207. <https://doi.org/10.1016/j.pain.2008.01.025>
- Espie, C. A. (2002). Insomnia: Conceptual issues in the development, persistence, and treatment of sleep disorder in adults. *Annual Review of Psychology*, *53*, 215–243. <https://doi.org/10.1146/annurev.psych.53.100901.135243>
- Evans, M. A., Buysse, D. J., Marsland, A. L., Wright, A. G. C., Foust, J., Carroll, L. W., Kohli, N., Mehra, R., Jasper, A., Srinivasan, S., & Hall, M. H. (2021). Meta-analysis of age and actigraphy-assessed sleep characteristics across the lifespan. *Sleep*, *44*(9). <https://doi.org/10.1093/sleep/zsab088>
- Fabbri, M., Beracci, A., Martoni, M., Meneo, D., Tonetti, L., & Natale, V. (2021). Measuring subjective sleep quality: A review. *International Journal of Environmental Research and Public Health*, *18*(3). <https://doi.org/10.3390/ijerph18031082>
- Fagot, D., Mella, N., Borella, E., Ghisletta, P., Lecerf, T., & Ribaupierre, A. de (2018). Intra-individual variability from a lifespan perspective: A comparison of latency and accuracy measures. *Journal of Intelligence*, *6*(1), 16. <https://doi.org/10.3390/jintelligence6010016>
- Fairholme, C. P., & Manber, R. (2015). Sleep, emotions, and emotion regulation: An overview. In K. A. Babson & M. T. Feldner (Eds.), *Sleep and affect: Assessment, theory, and clinical implications* (pp. 45–61). Academic Press. <https://doi.org/10.1016/B978-0-12-417188-6.00003-7>
- Fank, F., Da Pereira, F. S., Dos Santos, L., Mello, M. T. de, & Mazo, G. Z. (2022). Effects of exercise on sleep in older adults: an overview of systematic reviews and meta-analyses. *Journal of Aging and Physical Activity*, 1–17. <https://doi.org/10.1123/japa.2021-0444>

- Fayaz, A., Croft, P., Langford, R. M., Donaldson, L. J., & Jones, G. T. (2016). Prevalence of chronic pain in the UK: A systematic review and meta-analysis of population studies. *BMJ Open*, 6(6), e010364. <https://doi.org/10.1136/bmjopen-2015-010364>
- Federal Institute for Population Research. *Anteile der Altersgruppen unter 20 Jahren, ab 65 Jahre und ab 80 Jahre (1871-2060) [Percentage of Age Groups under 20 years, over 65 years and over 80 years, 1871-2060]*. <https://www.bib.bund.de/Permalink.html?id=10203338>
- Feldman Barrett, L., & Russell, J. A. (1998). Independence and bipolarity in the structure of current affect. *Journal of Personality and Social Psychology*, 74(4), 967–984. <https://doi.org/10.1037/0022-3514.74.4.967>
- Fenn, K. M., Nusbaum, H. C., & Margoliash, D. (2003). Consolidation during sleep of perceptual learning of spoken language. *Nature*, 425, 614–616. <https://doi.org/10.1038/nature01951>
- Fernández-Ballesteros, R. (2019). The concept of successful aging and related terms. In R. Fernández Ballesteros, A. Benetos, & J.-M. Robine (Eds.), *Cambridge handbooks in psychology. The Cambridge handbook of successful aging* (pp. 6–22). Cambridge University Press. <https://doi.org/10.1017/9781316677018.002>
- Ferrarelli, F., Kaskie, R., Laxminarayan, S., Ramakrishnan, S., Reifman, J., & Germain, A. (2019). An increase in sleep slow waves predicts better working memory performance in healthy individuals. *NeuroImage*, 191, 1–9. <https://doi.org/10.1016/j.neuroimage.2019.02.020>
- Fillingim, R. B., Loeser, J. D., Baron, R., & Edwards, R. R. (2016). Assessment of Chronic Pain: Domains, Methods, and Mechanisms. *The Journal of Pain*, 17(9, Suppl. 2), T10–T20. <https://doi.org/10.1016/j.jpain.2015.08.010>
- Finkel, D., Reynolds, C. A., McArdle, J. J., Gatz, M., & Pedersen, N. L. (2003). Latent growth curve analyses of accelerating decline in cognitive abilities in late adulthood. *Developmental Psychology*, 39(3), 535–550. <https://doi.org/10.1037/0012-1649.39.3.535>
- Flueckiger, L., Lieb, R., Meyer, A. H., Witthauer, C., & Mata, J. (2016). The importance of physical activity and sleep for affect on stressful days: Two intensive longitudinal studies. *Emotion*, 16(4), 488–497. <https://doi.org/10.1037/emo0000143>
- Flueckiger, L., Lieb, R., Meyer, A. H., Witthauer, C., & Mata, J. (2017). Day-to-day variations in health behaviors and daily functioning: Two intensive longitudinal studies. *Journal of Behavioral Medicine*, 40(2), 307–319. <https://doi.org/10.1007/s10865-016-9787-x>
- Foley, D. J., Ancoli-Israel, S., Britz, P., & Walsh, J. (2004). Sleep disturbances and chronic disease in older adults: Results of the 2003 National Sleep Foundation Sleep in America Survey: Results of the 2003 National Sleep Foundation Sleep in America Survey. *Journal of Psychosomatic Research*, 56(5), 497–502. <https://doi.org/10.1016/j.jpsychores.2004.02.010>

- Foley, D. J., Monjan, A. A., Brown, S. L., Simonsick, E. M., Wallace, R. B., & Blazer, D. G. (1995). Sleep complaints among elderly persons: An epidemiologic study of three communities. *Sleep, 18*(6), 425–432. <https://doi.org/10.1093/sleep/18.6.425>
- Fredrickson, B. L. (2004). The broaden-and-build theory of positive emotions. *Philosophical Transactions of the Royal Society B, Biological Sciences, 359*(1149), 1367–1378. <https://doi.org/10.1098/rstb.2004.1512>
- French, D. J., Sargent-Cox, K., & Luszcz, M. A. (2012). Correlates of subjective health across the aging lifespan: Understanding self-rated health in the oldest old. *Journal of Aging and Health, 24*(8), 1449–1469. <https://doi.org/10.1177/0898264312461151>
- Frenda, S. J., & Fenn, K. M. (2016). Sleep less, think worse: the effect of sleep deprivation on working memory. *Journal of Applied Research in Memory and Cognition, 5*(4), 463–469. <https://doi.org/10.1016/j.jarmac.2016.10.001>
- Frumkin, M. R., & Rodebaugh, T. L. (2021). The role of affect in chronic pain: A systematic review of within-person symptom dynamics. *Journal of Psychosomatic Research, 147*, 110527. <https://doi.org/10.1016/j.jpsychores.2021.110527>
- Gadie, A., Shafto, M., Leng, Y., & Kievit, R. A. (2017). How are age-related differences in sleep quality associated with health outcomes? An epidemiological investigation in a UK cohort of 2406 adults. *BMJ Open, 7*(7), e014920. <https://doi.org/10.1136/bmjopen-2016-014920>
- Gamaldo, A. A., Allaire, J. C., & Whitfield, K. E. (2010). Exploring the within-person coupling of sleep and cognition in older African Americans. *Psychology and Aging, 25*(4), 851–857. <https://doi.org/10.1037/a0021378>
- Garbarino, S., Lanteri, P., Prada, V., Falkenstein, M., & Sannita, W. G. (2021). Circadian rhythms, sleep, and aging. *Journal of Psychophysiology, 35*(3), 129–138. <https://doi.org/10.1027/0269-8803/a000267>
- Garcia, C., Zhang, L., Holt, K., Hardeman, R., & Peterson, B. (2014). Latina adolescent sleep and mood: An ecological momentary assessment pilot study. *Journal of Child and Adolescent Psychiatric Nursing, 27*(3), 132–141. <https://doi.org/10.1111/jcap.12082>
- Garrison, K. E., & Schmeichel, B. J. (2020). Getting over it: Working memory capacity and affective responses to stressful events in daily life. *Emotion, 22*(3), 418–429. <https://doi.org/10.1037/emo0000755>
- Gelman, A., & Rubin, D. B. (1992). Inference from Iterative Simulation Using Multiple Sequences. *Statistical Science, 7*(4), 457–472. <http://www.jstor.org/stable/2246093>
- Gerhardsson, A., Fischer, H., Lekander, M., Kecklund, G., Axelsson, J., Åkerstedt, T., & Schwarz, J. (2019). Positivity effect and working memory performance remains intact in older adults

- after sleep deprivation. *Frontiers in Psychology*, *10*, 605.  
<https://doi.org/10.3389/fpsyg.2019.00605>
- Gerhart, J. I., Burns, J. W., Post, K. M., Smith, D. A., Porter, L. S., Burgess, H. J., Schuster, E., Buvanendran, A., Fras, A. M., & Keefe, F. J. (2017). Relationships between sleep quality and pain-related factors for people with chronic low back pain: Tests of reciprocal and time of day effects. *Annals of Behavioral Medicine*, *51*(3), 365–375. <https://doi.org/10.1007/s12160-016-9860-2>
- Gerstorf, D., Hülür, G., Wagner, G. G., Kunzmann, U., & Ram, N. (2018). Terminal change across facets of affective experience and domain satisfaction: Commonalities, differences, and bittersweet emotions at the end of life. *Developmental Psychology*, *54*(12), 2382–2402.  
<https://doi.org/10.1037/dev0000599>
- Girschik, J., Fritschi, L., Heyworth, J., & Waters, F. (2012). Validation of self-reported sleep against actigraphy. *Journal of Epidemiology*, *22*(5), 462–468.  
<https://doi.org/10.2188/jea.je20120012>
- Goldstein, A. N., & Walker, M. P. (2014). The role of sleep in emotional brain function. *Annual Review of Clinical Psychology*, *10*, 679–708. <https://doi.org/10.1146/annurev-clinpsy-032813-153716>
- Gordon, A. M., Carrillo, B., & Barnes, C. M. (2021). Sleep and social relationships in healthy populations: A systematic review. *Sleep Medicine Reviews*, *57*, 101428.  
<https://doi.org/10.1016/j.smrv.2021.101428>
- Gorgoni, M., D'Atri, A., Lauri, G., Rossini, P. M., Ferlazzo, F., & Gennaro, L. de (2013). Is sleep essential for neural plasticity in humans, and how does it affect motor and cognitive recovery? *Neural Plasticity*, *2013*, 103949. <https://doi.org/10.1155/2013/103949>
- Gothe, N. P., Ehlers, D. K., Salerno, E. A., Fanning, J., Kramer, A. F., & McAuley, E. (2020). Physical activity, sleep and quality of life in older adults: Influence of physical, mental and social well-being. *Behavioral Sleep Medicine*, *18*(6), 797–808.  
<https://doi.org/10.1080/15402002.2019.1690493>
- Griffin, S. C., Ravyts, S. G., Bouchtein, E., Ulmer, C. S., Leggett, M. K., Dzierzewski, J. M., & Calhoun, P. S. (2021). Sleep disturbance and pain in U.S. Adults over 50: Evidence for reciprocal, longitudinal effects. *Sleep Medicine*, *86*, 32–39.  
<https://doi.org/10.1016/j.sleep.2021.08.006>
- Gross, J. J. (1998). The emerging field of emotion regulation: An integrative review: An Integrative Review. *Review of General Psychology*, *2*(3), 271–299. <https://doi.org/10.1037/1089-2680.2.3.271>

- Grossi, G., Jeding, K., Söderström, M., Osika, W., Levander, M., & Perski, A. (2015). Self-reported sleep lengths  $\geq 9$  hours among Swedish patients with stress-related exhaustion: Associations with depression, quality of sleep and levels of fatigue. *Nordic Journal of Psychiatry*, *69*(4), 292–299. <https://doi.org/10.3109/08039488.2014.973442>
- Gruber, R., & Cassoff, J. (2014). The interplay between sleep and emotion regulation: Conceptual framework empirical evidence and future directions. *Current Psychiatry Reports*, *16*(11), 500. <https://doi.org/10.1007/s11920-014-0500-x>
- Gui, W.-J., Li, H.-J., Guo, Y.-H., Peng, P., Lei, X., & Yu, J. (2017). Age-related differences in sleep-based memory consolidation: A meta-analysis. *Neuropsychologia*, *97*, 46–55. <https://doi.org/10.1016/j.neuropsychologia.2017.02.001>
- Gyasi, R. M., Adjakloe, Y. D. A., Siaw, L. P., James, P. B., Amoah, P. A., Abass, K., Adu-Gyamfi, S., & Phillips, D. R. (2022). The effect-modification of physical activity on the association of pain with impaired physical function in aging adults. *Experimental Gerontology*, *163*, 111791. <https://doi.org/10.1016/j.exger.2022.111791>
- Haack, M., Simpson, N., Sethna, N., Kaur, S., & Mullington, J. (2020). Sleep deficiency and chronic pain: Potential underlying mechanisms and clinical implications. *Neuropsychopharmacology*, *45*(1), 205–216. <https://doi.org/10.1038/s41386-019-0439-z>
- Haimov, I., & Shatil, E. (2013). Cognitive training improves sleep quality and cognitive function among older adults with insomnia. *PLOS ONE*, *8*(4), e61390. <https://doi.org/10.1371/journal.pone.0061390>
- Hale, L., Troxel, W., & Buysse, D. J. (2020). Sleep health: An opportunity for public health to address health equity. *Annual Review of Public Health*, *41*(1), 81–99. <https://doi.org/10.1146/annurev-publhealth-040119-094412>
- Hamer, M., Muniz Terrera, G., & Demakakos, P. (2018). Physical activity and trajectories in cognitive function: English Longitudinal Study of Ageing. *Journal of Epidemiology and Community Health*, *72*(6), 477–483. <https://doi.org/10.1136/jech-2017-210228>
- Hamilton, N. A., Catley, D., & Karlson, C. (2007). Sleep and the affective response to stress and pain. *Health Psychology*, *26*(3), 288–295. <https://doi.org/10.1037/0278-6133.26.3.288>
- Häusler, N., Marques-Vidal, P., Haba-Rubio, J., & Heinzer, R. (2019). Does sleep predict next-day napping or does napping influence same-day nocturnal sleep? Results of a population-based ecological momentary assessment study. *Sleep Medicine*, *61*, 31–36. <https://doi.org/10.1016/j.sleep.2019.04.014>
- Hayashino, Y., Yamazaki, S., Takegami, M., Nakayama, T., Sokejima, S., & Fukuhara, S. (2010). Association between number of comorbid conditions, depression, and sleep quality using



- the Pittsburgh Sleep Quality Index: Results from a population-based survey. *Sleep Medicine*, *11*(4), 366–371. <https://doi.org/10.1016/j.sleep.2009.05.021>
- Hirshkowitz, M., Whiton, K., Albert, S. M., Alessi, C., Bruni, O., DonCarlos, L., Hazen, N., Herman, J., Adams Hillard, P. J., Katz, E. S., Kheirandish-Gozal, L., Neubauer, D. N., O'Donnell, A. E., Ohayon, M., Peever, J., Rawding, R., Sachdeva, R. C., Setters, B., Vitiello, M. V., & Ware, J. C. (2015). National Sleep Foundation's updated sleep duration recommendations: Final report. *Sleep Health*, *1*(4), 233–243. <https://doi.org/10.1016/j.sleh.2015.10.004>
- Hoffman, L., & Stawski, R. S. (2009). Persons as contexts: Evaluating between-person and within-person effects in longitudinal analysis. *Research in Human Development*, *6*(2-3), 97–120. <https://doi.org/10.1080/15427600902911189>
- Hofmann, W., Gschwendner, T., Friese, M., Wiers, R. W., & Schmitt, M. (2008). Working memory capacity and self-regulatory behavior: Toward an individual differences perspective on behavior determination by automatic versus controlled processes. *Journal of Personality and Social Psychology*, *95*(4), 962–977. <https://doi.org/10.1037/a0012705>
- Holanda, F. W. N., & Almondes, K. M. de (2016). Sleep and executive functions in older adults: A systematic review. *Dementia & Neuropsychologia*, *10*(3), 185–197. <https://doi.org/10.1590/S1980-5764-2016DN1003004>
- Hoppmann, C. A., Pauly, T., Michalowski, V. I., & Nater, U. M. (2018). Everyday salivary cortisol as a biomarker method in lifespan developmental methodology. In B. Knight (Ed.), *Oxford Research Encyclopedia of Psychology*. Oxford University Press. <https://doi.org/10.1093/acrefore/9780190236557.013.353>
- Hot, P., Zsoldos, I., & Carrier, J. (2015). The relationship between sleep and emotion among the elderly. In K. A. Babson & M. T. Feldner (Eds.), *Sleep and affect: Assessment, theory, and clinical implications* (pp. 441–460). Academic Press. <https://doi.org/10.1016/B978-0-12-417188-6.00020-7>
- Hua, J., Sun, H., & Shen, Y. (2020). Improvement in sleep duration was associated with higher cognitive function: A new association. *Aging*, *12*(20), 20623–20644. <https://doi.org/10.18632/aging.103948>
- Hultsch, D. F., MacDonald, S. W. S., & Dixon, R. A. (2002). Variability in reaction time performance of younger and older adults. *The Journals of Gerontology: Series B*, *57*(2), 101–115. <https://doi.org/10.1093/geronb/57.2.p101>
- Hwang, H. R., & Kim, Y.-J. (2020). Effects of sleep patterns on the subjective health status in older men from the 7th Korea National Health and Nutrition Examination Survey, 2016. *Annals of Geriatric Medicine and Research*, *24*(2), 107–114. <https://doi.org/10.4235/agmr.20.0008>

- Ilkowska, M., & Engle, R. W. (2010). Trait and state differences in working memory capacity. In A. Gruszka, G. Matthews, & B. Szymura (Eds.), *Handbook of individual differences in cognition: Attention, memory, and executive control* (pp. 295–320). Springer New York. [https://doi.org/10.1007/978-1-4419-1210-7\\_18](https://doi.org/10.1007/978-1-4419-1210-7_18)
- Irwin, M. R., Olmstead, R., Carrillo, C., Sadeghi, N., Fitzgerald, J. D., Ranganath, V. K., & Nicassio, P. M. (2012). Sleep loss exacerbates fatigue, depression, and pain in rheumatoid arthritis. *Sleep*, *35*(4), 537–543. <https://doi.org/10.5665/sleep.1742>
- Isaacowitz, D. M., & Smith, J. (2003). Positive and negative affect in very old age. *The Journals of Gerontology: Series B*, *58*(3), P143-52. <https://doi.org/10.1093/geronb/58.3.p143>
- Itani, O., Jike, M., Watanabe, N., & Kaneita, Y. (2017). Short sleep duration and health outcomes: A systematic review, meta-analysis, and meta-regression. *Sleep Medicine*, *32*, 246–256. <https://doi.org/10.1016/j.sleep.2016.08.006>
- Jaeggi, S. M., Buschkuhl, M., Jonides, J., & Perrig, W. J. (2008). Improving fluid intelligence with training on working memory. *Proceedings of the National Academy of Sciences of the United States of America*, *105*(19), 6829–6833. <https://doi.org/10.1073/pnas.0801268105>
- Jike, M., Itani, O., Watanabe, N., Buysse, D. J., & Kaneita, Y. (2018). Long sleep duration and health outcomes: A systematic review, meta-analysis and meta-regression. *Sleep Medicine Reviews*, *39*, 25–36. <https://doi.org/10.1016/j.smr.2017.06.011>
- Jong, K. de, Moerbeek, M., & van der Leeden, R. (2010). A priori power analysis in longitudinal three-level multilevel models: An example with therapist effects. *Psychotherapy Research*, *20*(3), 273–284. <https://doi.org/10.1080/10503300903376320>
- Kaplan, K. A., Hirshman, J., Hernandez, B., Stefanick, M. L., Hoffman, A. R., Redline, S., Ancoli-Israel, S., Stone, K., Friedman, L., & Zeitzer, J. M. (2017). When a gold standard isn't so golden: Lack of prediction of subjective sleep quality from sleep polysomnography. *Biological Psychology*, *123*, 37–46. <https://doi.org/10.1016/j.biopsycho.2016.11.010>
- Katz, S., & Calasanti, T. (2015). Critical perspectives on successful aging: Does it "appeal more than it illuminates"? *The Gerontologist*, *55*(1), 26–33. <https://doi.org/10.1093/geront/gnu027>
- Kaufmann, C., Agalawatta, N., Bell, E., & S Malhi, G. (2020). Getting emotional about affect and mood. *The Australian and New Zealand Journal of Psychiatry*, *54*(8), 850–852. <https://doi.org/10.1177/0004867420943943>
- Kekäläinen, T., Freund, A. M., Sipilä, S., & Kokko, K. (2020). Cross-sectional and longitudinal associations between leisure time physical activity, mental well-being and subjective health in middle adulthood. *Applied Research in Quality of Life*, *15*(4), 1099–1116. <https://doi.org/10.1007/s11482-019-09721-4>

- Kessler, E.-M., & Staudinger, U. M. (2009). Affective experience in adulthood and old age: The role of affective arousal and perceived affect regulation. *Psychology and Aging, 24*(2), 349–362. <https://doi.org/10.1037/a0015352>
- Killgore, W. D. S., & Weber, M. (2014). Sleep deprivation and cognitive performance. In M. T. Bianchi (Ed.), *Sleep deprivation and disease: Effects on the body, brain and behavior* (pp. 209–229). Springer New York. [https://doi.org/10.1007/978-1-4614-9087-6\\_16](https://doi.org/10.1007/978-1-4614-9087-6_16)
- Kirkegaard Thomsen, D. (2006). The association between rumination and negative affect: A review. *Cognition & Emotion, 20*(8), 1216–1235. <https://doi.org/10.1080/02699930500473533>
- Kline, C. (2013). Polysomnography. In M. D. Gellman & J. R. Turner (Eds.), *Springer reference. Encyclopedia of Behavioral Medicine* (pp. 1501–1504). Springer New York. [https://doi.org/10.1007/978-1-4419-1005-9\\_825](https://doi.org/10.1007/978-1-4419-1005-9_825)
- Knoll, N., Keller, J., Luszczynska, A., Scholz, U., Röcke, C., Schrader, M., & Heckhausen, J. (2020a). Control Strategies and Daily Affect. *GeroPsych, 33*(3), 155–169. <https://doi.org/10.1024/1662-9647/A000229>
- Knoll, N., Keller, J., Luszczynska, A., Scholz, U., Röcke, C., Schrader, M., & Heckhausen, J. (2020b). Control strategies and daily affect. *GeroPsych, 33*(3), 155–169. <https://doi.org/10.1024/1662-9647/A000229>
- Koffel, E., McCurry, S. M., Smith, M. T [Michael T.], & Vitiello, M. V. (2019). Improving pain and sleep in middle-aged and older adults: The promise of behavioral sleep interventions. *Pain, 160*(3), 529–534. <https://doi.org/10.1097/j.pain.0000000000001423>
- Könen, T., Dirk, J., Leonhardt, A., & Schmiedek, F. (2016). The interplay between sleep behavior and affect in elementary school children's daily life. *Journal of Experimental Child Psychology, 150*, 1–15. <https://doi.org/10.1016/j.jecp.2016.04.003>
- Könen, T., Dirk, J., & Schmiedek, F. (2015). Cognitive benefits of last night's sleep: Daily variations in children's sleep behavior are related to working memory fluctuations. *Journal of Child Psychology and Psychiatry, and Allied Disciplines, 56*(2), 171–182. <https://doi.org/10.1111/jcpp.12296>
- Konjarski, M., Murray, G., Lee, V. V., & Jackson, M. L. (2018). Reciprocal relationships between daily sleep and mood: A systematic review of naturalistic prospective studies. *Sleep Medicine Reviews, 42*, 47–58. <https://doi.org/10.1016/j.smr.2018.05.005>
- Krause, A. J., Prather, A. A., Wager, T. D., Lindquist, M. A., & Walker, M. P. (2019). The pain of sleep loss: A brain characterization in humans. *The Journal of Neuroscience, 39*(12), 2291–2300. <https://doi.org/10.1523/JNEUROSCI.2408-18.2018>

- Krizan, Z., & Hisler, G. (2021). The Iowa Resistance to Sleeplessness Test (iREST). *Sleep Health*, 7(2), 229–237. <https://doi.org/10.1016/j.sleh.2020.12.002>
- Krystal, A. D., & Edinger, J. D. (2008). Measuring sleep quality. *Sleep Medicine*, 9, S10–S17. [https://doi.org/10.1016/S1389-9457\(08\)70011-X](https://doi.org/10.1016/S1389-9457(08)70011-X)
- Kudielka, B. M., Gierens, A., Hellhammer, D. H., Wüst, S., & Schlotz, W. (2012). Salivary cortisol in ambulatory assessment--some dos, some don'ts, and some open questions. *Psychosomatic Medicine*, 74(4), 418–431. <https://doi.org/10.1097/PSY.0b013e31825434c7>
- Kunzmann, U., Katzorreck, M., Wieck, C., Schilling, O. K., Lücke, A. J., & Gerstorf, D. (2022). Emotion regulation in old and very old age. *Emotion*. Advance online publication. <https://doi.org/10.1037/emo0001075>
- Kunzmann, U., Little, T. D., & Smith, J. (2000). Is age-related stability of subjective well-being a paradox? Cross-sectional and longitudinal evidence from the Berlin Aging Study. *Psychology and Aging*, 15(3), 511–526. <https://doi.org/10.1037//0882-7974.15.3.511>
- Kuriyama, K., Mishima, K., Suzuki, H., Aritake, S., & Uchiyama, M. (2008). Sleep accelerates the improvement in working memory performance. *The Journal of Neuroscience*, 28(40), 10145–10150. <https://doi.org/10.1523/JNEUROSCI.2039-08.2008>
- Kurth, F., Cherbuin, N., & Luders, E. (2017). Aging mindfully to minimize cognitive decline. *Journal of Cognitive Enhancement*, 1(2), 108–114. <https://doi.org/10.1007/s41465-017-0027-2>
- Kusztor, A., Raud, L., Juel, B. E., Nilsen, A. S., Storm, J. F., & Huster, R. J. (2019). Sleep deprivation differentially affects subcomponents of cognitive control. *Sleep*, 42(4). <https://doi.org/10.1093/sleep/zsz016>
- Kuzma, E., Pantel, J., & Schröder, J [J.]. (2012). Prävention psychischer Krankheiten im Alter. In H.-W. Wahl, C. Tesch-Römer, & J. P. Ziegelmann (Eds.), *Angewandte Gerontologie: Interventionen für ein gutes Altern in 100 Schlüsselbegriffen* (2nd ed., pp. 188–193). Kohlhammer.
- Lallukka, T., Sivertsen, B., Kronholm, E., Bin, Y. S., Øverland, S., & Glozier, N. (2018). Association of sleep duration and sleep quality with the physical, social, and emotional functioning among Australian adults. *Sleep Health*, 4(2), 194–200. <https://doi.org/10.1016/j.sleh.2017.11.006>
- Le Bon, O., Staner, L., Hoffmann, G., Dramaix, M., San Sebastian, I., Murphy, J. R., Kentos, M., Pelc, I., & Linkowski, P. (2001). The first-night effect may last more than one night. *Journal of Psychiatric Research*, 35(3), 165–172. [https://doi.org/10.1016/S0022-3956\(01\)00019-X](https://doi.org/10.1016/S0022-3956(01)00019-X)

- Lee, E. E. (2019). Aging successfully and healthfully. *International Psychogeriatrics*, *31*(4), 439–441. <https://doi.org/10.1017/S1041610219000012>
- Lee, E., & Hong, S. (2021). Adequate sample sizes for a three-level growth model. *Frontiers in Psychology*, *12*, 685496. <https://doi.org/10.3389/fpsyg.2021.685496>
- Lee, J. A., Sunwoo, S., Kim, Y. S., Yu, B. Y., Park, H. K., Jeon, T. H., & Yoo, B. W. (2016). The Effect of Sleep Quality on the Development of Type 2 Diabetes in Primary Care Patients. *Journal of Korean Medical Science*, *31*(2), 240–246. <https://doi.org/10.3346/jkms.2016.31.2.240>
- Leger, K. A., Charles, S. T., & Almeida, D. M. (2018). Let it go: Lingering negative affect in response to daily stressors is associated with physical health years later. *Psychological Science*, *29*(8), 1283–1290. <https://doi.org/10.1177/0956797618763097>
- Lehrer, H. M., Yao, Z., Krafty, R. T., Evans, M. A., Buysse, D. J., Kravitz, H. M., Matthews, K. A., Gold, E. B., Harlow, S. D., Samuelsson, L. B., & Hall, M. H. (2022). Comparing polysomnography, actigraphy, and sleep diary in the home environment: The Study of Women's Health Across the Nation (SWAN) Sleep Study. *Sleep Advances*, *3*(1), zpac001. <https://doi.org/10.1093/sleepadvances/zpac001>
- Lekander, M., Andreasson, A. N., Kecklund, G., Ekman, R., Ingre, M., Åkerstedt, T., & Axelsson, J. (2013). Subjective health perception in healthy young men changes in response to experimentally restricted sleep and subsequent recovery sleep. *Brain, Behavior, and Immunity*, *34*, 43–46. <https://doi.org/10.1016/j.bbi.2013.06.005>
- Leong, R. L. F., Lo, J. C., & Chee, M. W. L. (2021). Sleep-dependent prospective memory consolidation is impaired with aging. *Sleep*, *44*(9), zsab069. <https://doi.org/10.1093/sleep/zsab069>
- Lewis, L. D. (2021). The interconnected causes and consequences of sleep in the brain. *Science*, *374*(6567), 564–568. <https://doi.org/10.1126/science.abi8375>
- Li, J., Vitiello, M. V., & Gooneratne, N. S. (2018). Sleep in normal aging. *Sleep Medicine Clinics*, *13*(1), 1–11. <https://doi.org/10.1016/j.jsmc.2017.09.001>
- Li, L., Gan, Y., Zhou, X., Jiang, H., Zhao, Y., Tian, Q., He, Y., Liu, Q., Mei, Q., Wu, C., & Lu, Z. (2021). Insomnia and the risk of hypertension: A meta-analysis of prospective cohort studies. *Sleep Medicine Reviews*, *56*, 101403. <https://doi.org/10.1016/j.smr.2020.101403>
- Lim, J., & Dinges, D. F. (2010). A meta-analysis of the impact of short-term sleep deprivation on cognitive variables. *Psychological Bulletin*, *136*(3), 375–389. <https://doi.org/10.1037/a0018883>
- Lin, H. (2020). Probing two-way moderation effects: A review of software to easily plot Johnson-Neyman figures. *Structural Equation Modeling: A Multidisciplinary Journal*, *27*(3), 494–502. <https://doi.org/10.1080/10705511.2020.1732826>

- Lippman, S., Gardener, H., Rundek, T., Seixas, A., Elkind, M. S. V., Sacco, R. L., Wright, C. B., & Ramos, A. R. (2017). Short sleep is associated with more depressive symptoms in a multi-ethnic cohort of older adults. *Sleep Medicine*, *40*, 58–62.  
<https://doi.org/10.1016/j.sleep.2017.09.019>
- Liu, Y., Wheaton, A. G., Croft, J. B., Xu, F., Cunningham, T. J., & Greenlund, K. J. (2018). Relationship between sleep duration and self-reported health-related quality of life among US adults with or without major chronic diseases. *Sleep Health*, *4*(3), 265–272.  
<https://doi.org/10.1016/j.sleh.2018.02.002>
- Lo, J. C., Groeger, J. A., Cheng, G. H., Dijk, D.-J., & Chee, M. W. L. (2016). Self-reported sleep duration and cognitive performance in older adults: A systematic review and meta-analysis. *Sleep Medicine*, *17*, 87–98. <https://doi.org/10.1016/j.sleep.2015.08.021>
- Lövdén, M., Li, S.-C., Shing, Y. L., & Lindenberger, U. (2007). Within-person trial-to-trial variability precedes and predicts cognitive decline in old and very old age: Longitudinal data from the Berlin Aging Study. *Neuropsychologia*, *45*(12), 2827–2838.  
<https://doi.org/10.1016/j.neuropsychologia.2007.05.005>
- Lowe, C. J., Safati, A., & Hall, P. A. (2017). The neurocognitive consequences of sleep restriction: A meta-analytic review. *Neuroscience and Biobehavioral Reviews*, *80*, 586–604.  
<https://doi.org/10.1016/j.neubiorev.2017.07.010>
- Lu, H., Chan, S. S. M., & Lam, L. C. W. (2016). Associations between intra-individual variability of reaction time and cognitive function in cognitively normal senior adults: Still beyond good or bad? *Geriatrics*, *1*(2), 13. <https://doi.org/10.3390/geriatrics1020013>
- Lücke, A. J., Wrzus, C., Gerstorff, D., Kunzmann, U., Katzorreck, M., Kolodziejczak, K., Ram, N., Hoppmann, C., & Schilling, O. K. (in press). Good night – good day? Bidirectional links of daily sleep quality with negative affect and stress reactivity in old age. *Psychology and Aging*.
- Magee, C. A., Caputi, P., & Iverson, D. C. (2011). Relationships between self-rated health, quality of life and sleep duration in middle aged and elderly Australians. *Sleep Medicine*, *12*(4), 346–350. <https://doi.org/10.1016/j.sleep.2010.09.013>
- Marcusson-Clavertz, D., Sliwinski, M. J., Buxton, O. M., Kim, J., Almeida, D. M., & Smyth, J. M. (2022). Relationships between daily stress responses in everyday life and nightly sleep. *Journal of Behavioral Medicine*, 1–15. <https://doi.org/10.1007/s10865-021-00281-3>
- Mauss, I. B., Troy, A. S., & LeBourgeois, M. K. (2013). Poorer sleep quality is associated with lower emotion-regulation ability in a laboratory paradigm. *Cognition & Emotion*, *27*(3), 567–576.  
<https://doi.org/10.1080/02699931.2012.727783>

- McCrae, C. S., Dzierzewski, J. M., McNamara, J. P. H., Vathauer, K. E., Roth, A. J., & Rowe, M. A. (2016). Changes in sleep predict changes in affect in older caregivers of individuals with alzheimer's dementia: A multilevel model approach. *The Journals of Gerontology: Series B*, *71*(3), 458–462. <https://doi.org/10.1093/geronb/gbul62>
- McCrae, C. S., McNamara, J. P. H., Rowe, M. A., Dzierzewski, J. M., Dirk, J., Marsiske, M., & Craggs, J. G. (2008). Sleep and affect in older adults: Using multilevel modeling to examine daily associations. *Journal of Sleep Research*, *17*(1), 42–53. <https://doi.org/10.1111/j.1365-2869.2008.00621.x>
- McNeish, D. (2018). Thanks coefficient alpha, we'll take it from here. *Psychological Methods*, *23*(3), 412–433. <https://doi.org/10.1037/met0000144>
- McNeish, D. (2020). Specifying location-scale models for heterogeneous variances as multilevel SEMs. *Organizational Research Methods*, *24*(3), 630–653. <https://doi.org/10.1177/1094428120913083>
- McNeish, D., & Hamaker, E. L. (2019). A primer on two-level dynamic structural equation models for intensive longitudinal data in Mplus. *Psychological Methods*, *25*(5), 610–635. <https://doi.org/10.1037/met0000250>
- Mednick, S. C., Cai, D. J., Shuman, T., Anagnostaras, S., & Wixted, J. T. (2011). An opportunistic theory of cellular and systems consolidation. *Trends in Neurosciences*, *34*(10), 504–514. <https://doi.org/10.1016/j.tins.2011.06.003>
- Mignot, E. (2008). Why we sleep: The temporal organization of recovery. *PLoS Biology*, *6*(4), e106. <https://doi.org/10.1371/journal.pbio.0060106>
- Minkel, J. D., Banks, S., Htaik, O., Moreta, M. C., Jones, C. W., McGlinchey, E. L., Simpson, N. S., & Dinges, D. F. (2012). Sleep deprivation and stressors: Evidence for elevated negative affect in response to mild stressors when sleep deprived. *Emotion*, *12*(5), 1015–1020. <https://doi.org/10.1037/a0026871>
- Motomura, Y., Kitamura, S., Oba, K., Terasawa, Y., Enomoto, M., Katayose, Y., Hida, A., Moriguchi, Y., Higuchi, S., & Mishima, K. (2013). Sleep debt elicits negative emotional reaction through diminished amygdala-anterior cingulate functional connectivity. *PLOS ONE*, *8*(2), e56578. <https://doi.org/10.1371/journal.pone.0056578>
- Mroczek, D. K., Stawski, R. S., Turiano, N. A., Chan, W., Almeida, D. M., Neupert, S. D., & Spiro, A. (2015). Emotional reactivity and mortality: Longitudinal findings From the VA normative aging study. *The Journals of Gerontology: Series B*, *70*(3), 398–406. <https://doi.org/10.1093/geronb/gbt107>
- Mu, C. X., & Lee, S [Soomi] (2022). The moderating role of trait and state mindfulness between daily sleep and physical pain symptoms: An ecological momentary assessment and

- actigraphy study. *Psychology & Health*, 1–18.  
<https://doi.org/10.1080/08870446.2022.2069245>
- Muthén, B., & Asparouhov, T. (2012). Bayesian structural equation modeling: A more flexible representation of substantive theory. *Psychological Methods*, 17(3), 313–335.  
<https://doi.org/10.1037/a0026802>
- Muthén, L. K., & Muthén, B. (1998-2017). *Mplus user's guide. Eighth edition*. Los Angeles, CA: Muthén & Muthén.
- Nakata, A., Takahashi, M., Otsuka, Y., & Swanson, N. G. (2010). Is self-rated health associated with blood immune markers in healthy individuals? *International Journal of Behavioral Medicine*, 17(3), 234–242. <https://doi.org/10.1007/s12529-010-9102-0>
- Nebes, R. D., Buysse, D. J., Halligan, E. M., Houck, P. R., & Monk, T. H. (2009). Self-reported sleep quality predicts poor cognitive performance in healthy older adults. *The Journals of Gerontology: Series B*, 64(2), 180–187. <https://doi.org/10.1093/geronb/gbn037>
- Neckelmann, D., Mykletun, A., & Dahl, A. A. (2007). Chronic insomnia as a risk factor for developing anxiety and depression. *Sleep*, 30(7), 873–880.  
<https://doi.org/10.1093/sleep/30.7.873>
- Nesselroade, J. R., Gerstorf, D., Hardy, S. A., & Ram, N. (2007). Idiographic filters for psychological constructs. *Measurement: Interdisciplinary Research & Perspective*, 5(4), 217–235. <https://doi.org/10.1080/15366360701741807>
- Neubauer, A. B., Voelke, M. C., Voss, A., & Mertens, U. K. (2020). Estimating reliability of within-person couplings in a multilevel framework. *Journal of Personality Assessment*, 102(1), 10–21. <https://doi.org/10.1080/00223891.2018.1521418>
- Newman, A. B., Enright, P. L., Manolio, T. A., Haponik, E. F., & Wahl, P. W. (1997). Sleep disturbance, psychosocial correlates, and cardiovascular disease in 5201 older adults: The Cardiovascular Health Study. *Journal of the American Geriatrics Society*, 45(1), 1–7.  
<https://doi.org/10.1111/j.1532-5415.1997.tb00970.x>
- Nicassio, P. M., Ormseth, S. R., Kay, M., Custodio, M., Irwin, M. R., Olmstead, R., & Weisman, M. H. (2012). The contribution of pain and depression to self-reported sleep disturbance in patients with rheumatoid arthritis. *Pain*, 153(1), 107–112.  
<https://doi.org/10.1016/j.pain.2011.09.024>
- O'Brien, E. M., Waxenberg, L. B., Atchison, J. W., Gremillion, H. A., Staud, R. M., McCrae, C. S., & Robinson, M. E. (2010). Negative mood mediates the effect of poor sleep on pain among chronic pain patients. *The Clinical Journal of Pain*, 26(4), 310–319.  
<https://doi.org/10.1097/AJP.0b013e3181c328e9>



- O'Brien, E. M., Waxenberg, L. B., Atchison, J. W., Gremillion, H. A., Staud, R. M., McCrae, C. S., & Robinson, M. E. (2011). Intraindividual variability in daily sleep and pain ratings among chronic pain patients: Bidirectional association and the role of negative mood. *The Clinical Journal of Pain*, 27(5), 425–433. <https://doi.org/10.1097/AJP.0b013e318208c8e4>
- Ohayon, M. M. (2004). Interactions between sleep normative data and sociocultural characteristics in the elderly. *Journal of Psychosomatic Research*, 56(5), 479–486. <https://doi.org/10.1016/j.psychores.2004.04.365>
- Ohayon, M. M., Carskadon, M. A., Guilleminault, C., & Vitiello, M. V. (2004). Meta-analysis of quantitative sleep parameters from childhood to old age in healthy individuals: Developing normative sleep values across the human lifespan. *Sleep*, 27(7), 1255–1273. <https://doi.org/10.1093/sleep/27.7.1255>
- Ong, A. D., Exner-Cortens, D., Riffin, C., Steptoe, A., Zautra, A., & Almeida, D. M. (2013). Linking stable and dynamic features of positive affect to sleep. *Annals of Behavioral Medicine*, 46(1), 52–61. <https://doi.org/10.1007/s12160-013-9484-8>
- Ong, J. C., & Moore, C. (2020). What do we really know about mindfulness and sleep health? *Current Opinion in Psychology*, 34, 18–22. <https://doi.org/10.1016/j.copsyc.2019.08.020>
- Ong, J. C., Xia, Y., Smith-Mason, C. E., & Manber, R. (2018). A randomized controlled trial of mindfulness meditation for chronic insomnia: effects on daytime symptoms and cognitive-emotional arousal. *Mindfulness*, 9(6), 1702–1712. <https://doi.org/10.1007/s12671-018-0911-6>
- Opdebeeck, C., Martyr, A., & Clare, L. (2016). Cognitive reserve and cognitive function in healthy older people: A meta-analysis. *Aging, Neuropsychology, and Cognition*, 23(1), 40–60. <https://doi.org/10.1080/13825585.2015.1041450>
- Paquet, C., Kergoat, M.-J., & Dubé, L. (2005). The role of everyday emotion regulation on pain in hospitalized elderly: Insights from a prospective within-day assessment. *Pain*, 115(3), 355–363. <https://doi.org/10.1016/j.pain.2005.03.024>
- Parra-Rizo, M. A., & Sanchís-Soler, G. (2021). Physical activity and the improvement of autonomy, functional ability, subjective health, and social relationships in women over the age of 60. *International Journal of Environmental Research and Public Health*, 18(13), 6926. <https://doi.org/10.3390/ijerph18136926>
- Patel, K. V., Guralnik, J. M., Dansie, E. J., & Turk, D. C. (2013). Prevalence and impact of pain among older adults in the United States: Findings from the 2011 National Health and Aging Trends Study. *Pain*, 154(12), 2649–2657. <https://doi.org/10.1016/j.pain.2013.07.029>

- Pauly, T., Kolodziejczak, K., Drewelies, J., Gerstorff, D., Ram, N., & Hoppmann, C. A. (2021). Political context is associated with everyday cortisol synchrony in older couples. *Psychoneuroendocrinology*, *124*, 105082. <https://doi.org/10.1016/j.psychoneu.2020.105082>
- Pe, M. L., Raes, F., & Kuppens, P. (2013). The cognitive building blocks of emotion regulation: Ability to update working memory moderates the efficacy of rumination and reappraisal on emotion. *PLOS ONE*, *8*(7), e69071. <https://doi.org/10.1371/journal.pone.0069071>
- Piazza, J. R., Charles, S. T., Sliwinski, M. J., Mogle, J., & Almeida, D. M. (2013). Affective reactivity to daily stressors and long-term risk of reporting a chronic physical health condition. *Annals of Behavioral Medicine*, *45*(1), 110–120. <https://doi.org/10.1007/s12160-012-9423-0>
- Pinquart, M. (2001a). Age differences in perceived positive affect, negative affect, and affect balance in middle and old age. *Journal of Happiness Studies*, *2*(4), 375–405. <https://doi.org/10.1023/A:1013938001116>
- Pinquart, M. (2001b). Correlates of subjective health in older adults: A meta-analysis. *Psychology and Aging*, *16*(3), 414–426. <https://doi.org/10.1037/0882-7974.16.3.414>
- Piper, A. T. (2016). Sleep duration and life satisfaction. *International Review of Economics*, *63*(4), 305–325. <https://doi.org/10.1007/s12232-016-0256-1>
- Raja, S. N., Carr, D. B., Cohen, M., Finnerup, N. B., Flor, H., Gibson, S., Keefe, F. J., Mogil, J. S., Ringkamp, M., Sluka, K. A., Song, X.-J., Stevens, B., Sullivan, M. D., Tutelman, P. R., Ushida, T., & Vader, K. (2020). The revised International Association for the Study of Pain definition of pain: Concepts, challenges, and compromises. *Pain*, *161*(9), 1976–1982. <https://doi.org/10.1097/j.pain.0000000000001939>
- Ramlee, F., Afolalu, E. F., & Tang, N. K. Y. (2018). Do people with chronic pain judge their sleep differently? A qualitative study. *Behavioral Sleep Medicine*, *16*(3), 259–271. <https://doi.org/10.1080/15402002.2016.1188393>
- Raymond, I., Nielsen, T. A., Lavigne, G., Manzini, C., & Choinière, M. (2001). Quality of sleep and its daily relationship to pain intensity in hospitalized adult burn patients. *Pain*, *92*(3), 381–388. [https://doi.org/10.1016/S0304-3959\(01\)00282-2](https://doi.org/10.1016/S0304-3959(01)00282-2)
- Ready, R. E., Marquez, D. X., & Akerstedt, A. (2009). Emotion in younger and older adults: Retrospective and prospective associations with sleep and physical activity. *Experimental Aging Research*, *35*(3), 348–368. <https://doi.org/10.1080/03610730902922184>
- Revelle, W. (2021). *psych* (Version 2.1.3) [Computer software]. Northwestern University. <https://CRAN.R-project.org/package=psych>
- Richards, A., Inslicht, S. S., Metzler, T. J., Mohlenhoff, B. S., Rao, M. N., O'Donovan, A., & Neylan, T. C. (2017). Sleep and cognitive performance from teens to old age: More is not better. *Sleep*, *40*(1). <https://doi.org/10.1093/sleep/zsw029>

- Richmond, L. L., Morrison, A. B., Chein, J. M., & Olson, I. R. (2011). Working memory training and transfer in older adults. *Psychology and Aging, 26*(4), 813–822.  
<https://doi.org/10.1037/a0023631>
- Riediger, M., & Rauers, A. (2014). Do everyday affective experiences differ throughout adulthood? A review of ambulatory-assessment evidence. In P. Verhaeghen & C. Hertzog (Eds.), *The Oxford Handbook of emotion, social cognition, and problem solving in adulthood* (pp. 61–82). Oxford University Press.
- Riediger, M., Wrzus, C., Klipker, K., Müller, V., Schmiedek, F., & Wagner, G. G. (2014). Outside of the laboratory: Associations of working-memory performance with psychological and physiological arousal vary with age: Associations of working-memory performance with psychological and physiological arousal vary with age. *Psychology and Aging, 29*(1), 103–114. <https://doi.org/10.1037/a0035766>
- Riediger, M., Wrzus, C., Schmiedek, F., Wagner, G. G., & Lindenberger, U. (2011). Is seeking bad mood cognitively demanding? Contra-hedonic orientation and working-memory capacity in everyday life. *Emotion, 11*(3), 656–665. <https://doi.org/10.1037/a0022756>
- Rights, J. D., & Sterba, S. K. (2019). Quantifying explained variance in multilevel models: An integrative framework for defining R-squared measures. *Psychological Methods, 24*(3), 309–338. <https://doi.org/10.1037/met0000184>
- Robertson, S., Myerson, J., & Hale, S. (2006). Are there age differences in intraindividual variability in working memory performance? *The Journals of Gerontology: Series B, 61*(1), P18-P24. <https://doi.org/10.1093/geronb/61.1.p18>
- RStudio Team. (2021). *RStudio* (Version 1.4) [Computer software]. RStudio Team. Boston, MA. <http://www.rstudio.com/>
- Sala, G., Aksayli, N. D., Tatlidil, K. S., Gondo, Y., & Gobet, F. (2019). Working memory training does not enhance older adults' cognitive skills: A comprehensive meta-analysis. *Intelligence, 77*, 101386. <https://doi.org/10.1016/j.intell.2019.101386>
- Salthouse, T. A. (1979). Adult age and the speed-accuracy trade-off. *Ergonomics, 22*(7), 811–821. <https://doi.org/10.1080/00140137908924659>
- Salthouse, T. A. (2019). Trajectories of normal cognitive aging. *Psychology and Aging, 34*(1), 17–24. <https://doi.org/10.1037/pag0000288>
- Santisteban, J. A., Brown, T. G., Ouimet, M. C., & Gruber, R. (2019). Cumulative mild partial sleep deprivation negatively impacts working memory capacity but not sustained attention, response inhibition, or decision making: A randomized controlled trial. *Sleep Health, 5*(1), 101–108. <https://doi.org/10.1016/j.sleh.2018.09.007>

- Sattari, N., Whitehurst, L. N., Ahmadi, M., & Mednick, S. C. (2019). Does working memory improvement benefit from sleep in older adults? *Neurobiology of Sleep and Circadian Rhythms*, 6, 53–61. <https://doi.org/10.1016/j.nbscr.2019.01.001>
- Sattler, C., Wahl, H.-W., Schröder, J [Johannes], Kruse, A., Schönknecht, P., Kunzmann, U., Braun, T., Degen, C., Nitschke, I., Rahmlow, W., Rammelsberg, P., Siebert, J. S., Tauber, B., Wendelstein, B., & Zenthöfer, A. (2017). Interdisciplinary Longitudinal Study on Adult Development and Aging (ILSE). In N. A. Pachana (Ed.), *Encyclopedia of Geropsychology* (pp. 1213–1222). Springer. [https://doi.org/10.1007/978-981-287-082-7\\_238](https://doi.org/10.1007/978-981-287-082-7_238)
- Schiavenato, M., & Craig, K. D. (2010). Pain assessment as a social transaction: Beyond the "gold standard". *The Clinical Journal of Pain*, 26(8), 667–676. <https://doi.org/10.1097/AJP.0b013e3181e72507>
- Schilling, O. K., Deeg, D. J. H., & Huisman, M. (2018). Affective well-being in the last years of life: The role of health decline. *Psychology and Aging*, 33(5), 739–753. <https://doi.org/10.1037/pag0000279>
- Schilling, O. K., & Diehl, M. (2015). Psychological vulnerability to daily stressors in old age: Results of short-term longitudinal studies. *Zeitschrift Für Gerontologie Und Geriatrie*, 48(6), 517–523. <https://doi.org/10.1007/s00391-015-0935-7>
- Schilling, O. K., Gerstorf, D., Lücke, A. J., Katzorreck, M., Wahc l, H.-W., Diehl, M., & Kunzmann, U. (2022). Emotional reactivity to daily stressors: Does stressor pile-up within a day matter for young-old and very old adults? *Psychology and Aging*, 37(2), 149–162. <https://doi.org/10.1037/pag0000667>
- Schmidt, M. H. (2014). The energy allocation function of sleep: A unifying theory of sleep, torpor, and continuous wakefulness. *Neuroscience and Biobehavioral Reviews*, 47, 122–153. <https://doi.org/10.1016/j.neubiorev.2014.08.001>
- Schmiedek, F., Hildebrandt, A., Lövdén, M., Wilhelm, O., & Lindenberger, U. (2009). Complex span versus updating tasks of working memory: The gap is not that deep. *Journal of Experimental Psychology. Learning, Memory, and Cognition*, 35(4), 1089–1096. <https://doi.org/10.1037/a0015730>
- Schmiedek, F., Lövdén, M., & Lindenberger, U. (2013). Keeping it steady: Older adults perform more consistently on cognitive tasks than younger adults. *Psychological Science*, 24(9), 1747–1754. <https://doi.org/10.1177/0956797613479611>
- Schrimpf, M., Liegl, G., Boeckle, M., Leitner, A., Geisler, P., & Pieh, C. (2015). The effect of sleep deprivation on pain perception in healthy subjects: A meta-analysis. *Sleep Medicine*, 16(11), 1313–1320. <https://doi.org/10.1016/j.sleep.2015.07.022>

- Schuurman, N. K., Ferrer, E., Boer-Sonnenschein, M. de, & Hamaker, E. L. (2016). How to compare cross-lagged associations in a multilevel autoregressive model. *Psychological Methods, 21*(2), 206–221. <https://doi.org/10.1037/met0000062>
- Schwarz, J., Axelsson, J., Gerhardsson, A., Tamm, S., Fischer, H., Kecklund, G., & Åkerstedt, T. (2019). Mood impairment is stronger in young than in older adults after sleep deprivation. *Journal of Sleep Research, 28*(4), e12801. <https://doi.org/10.1111/jsr.12801>
- Schwarz, J., Gerhardsson, A., van Leeuwen, W., Lekander, M., Ericson, M., Fischer, H., Kecklund, G., & Åkerstedt, T. (2018). Does sleep deprivation increase the vulnerability to acute psychosocial stress in young and older adults? *Psychoneuroendocrinology, 96*, 155–165. <https://doi.org/10.1016/j.psyneuen.2018.06.003>
- Scott, A. J., Webb, T. L., Martyn-St James, M., Rowse, G., & Weich, S. (2021). Improving sleep quality leads to better mental health: A meta-analysis of randomised controlled trials. *Sleep Medicine Reviews, 60*, 101556. <https://doi.org/10.1016/j.smr.2021.101556>
- Scott, S. B., Ram, N., Smyth, J. M., Almeida, D. M., & Sliwinski, M. J. (2017). Age differences in negative emotional responses to daily stressors depend on time since event. *Developmental Psychology, 53*(1), 177–190. <https://doi.org/10.1037/dev0000257>
- Scullin, M. K., & Bliwise, D. L. (2015). Sleep, cognition, and normal aging: Integrating a half century of multidisciplinary research. *Perspectives on Psychological Science, 10*(1), 97–137. <https://doi.org/10.1177/1745691614556680>
- Segerstrom, S. C. (2014). Affect and self-rated health: A dynamic approach with older adults. *Health Psychology, 33*(7), 720–728. <https://doi.org/10.1037/a0033506>
- Sella, E., Toffalini, E., Canini, L., & Borella, E. (2022). Non-pharmacological interventions targeting sleep quality in older adults: A systematic review and meta-analysis. *Aging & Mental Health, 1*–15. <https://doi.org/10.1080/13607863.2022.2056879>
- Shiffman, S., Stone, A. A., & Hufford, M. R. (2008). Ecological momentary assessment. *Annual Review of Clinical Psychology, 4*, 1–32. <https://doi.org/10.1146/annurev.clinpsy.3.022806.091415>
- Shimada, H., Park, H., Makizako, H., Doi, T., Lee, S [Sangyoon], & Suzuki, T. (2014). Depressive symptoms and cognitive performance in older adults. *Journal of Psychiatric Research, 57*, 149–156. <https://doi.org/10.1016/j.jpsychires.2014.06.004>
- Shing, Y. L., Schmiedek, F., Lövdén, M., & Lindenberger, U. (2012). Memory updating practice across 100 days in the COGITO study. *Psychology and Aging, 27*(2), 451–461. <https://doi.org/10.1037/a0025568>

- Shiota, M. N., & Levenson, R. W. (2009). Effects of aging on experimentally instructed detached reappraisal, positive reappraisal, and emotional behavior suppression. *Psychology and Aging, 24*(4), 890–900. <https://doi.org/10.1037/a0017896>
- Shipstead, Z., Redick, T. S., & Engle, R. W. (2012). Is working memory training effective? *Psychological Bulletin, 138*(4), 628–654. <https://doi.org/10.1037/a0027473>
- Shokri-Kojori, E., Wang, G.-J., Wiers, C. E., Demiral, S. B., Guo, M., Kim, S. W., Lindgren, E., Ramirez, V., Zehra, A., Freeman, C., Miller, G., Manza, P., Srivastava, T., Santi, S. de, Tomasi, D., Benveniste, H., & Volkow, N. D. (2018). B-Amyloid accumulation in the human brain after one night of sleep deprivation. *Proceedings of the National Academy of Sciences of the United States of America, 115*(17), 4483–4488. <https://doi.org/10.1073/pnas.1721694115>
- Siegler, R. S. (1994). Cognitive variability: A key to understanding cognitive development. *Current Directions in Psychological Science, 3*(1), 1–5. <https://doi.org/10.1111/1467-8721.ep10769817>
- Simoes Maria, M., Büla, C., Santos-Eggimann, B., Krief, H., Heinzer, R., & Seematter-Bagnoud, L. (2020). Sleep characteristics and self-rated health in older persons. *European Geriatric Medicine, 11*(1), 131–138. <https://doi.org/10.1007/s41999-019-00262-5>
- Simor, P., Krietsch, K. N., Köteles, F., & McCrae, C. S. (2015). Day-to-day variation of subjective sleep quality and emotional states among healthy university students--a 1-week prospective study. *International Journal of Behavioral Medicine, 22*(5), 625–634. <https://doi.org/10.1007/s12529-015-9464-4>
- Sin, N. L., Almeida, D. M., Crain, T. L., Kossek, E. E., Berkman, L. F., & Buxton, O. M. (2017). Bidirectional, temporal associations of sleep with positive events, affect, and stressors in daily life across a week. *Annals of Behavioral Medicine, 51*(3), 402–415. <https://doi.org/10.1007/s12160-016-9864-y>
- Sin, N. L., Graham-Engeland, J. E., Ong, A. D., & Almeida, D. M. (2015). Affective reactivity to daily stressors is associated with elevated inflammation. *Health Psychology, 34*(12), 1154–1165. <https://doi.org/10.1037/hea0000240>
- Sin, N. L., Rush, J., Buxton, O. M., & Almeida, D. M. (2021). Emotional vulnerability to short sleep predicts increases in chronic health conditions across 8 years. *Annals of Behavioral Medicine, 55*(12), 1231–1240. <https://doi.org/10.1093/abm/kaab018>
- Sin, N. L., Wen, J. H., Klaiber, P., Buxton, O. M., & Almeida, D. M. (2020). Sleep duration and affective reactivity to stressors and positive events in daily life. *Health Psychology, 39*(12), 1078–1088. <https://doi.org/10.1037/hea0001033>
- Slavish, D. C., Sliwinski, M. J., Smyth, J. M., Almeida, D. M., Lipton, R. B., Katz, M. J., & Graham-Engeland, J. E. (2018). Neuroticism, rumination, negative affect, and sleep: Examining

- between- and within-person associations. *Personality and Individual Differences*, *123*, 217–222. <https://doi.org/10.1016/j.paid.2017.11.023>
- Sliwinski, M. J., Almeida, D. M., Smyth, J., & Stawski, R. S. (2009). Intraindividual change and variability in daily stress processes: Findings from two measurement-burst diary studies. *Psychology and Aging*, *24*(4), 828–840. <https://doi.org/10.1037/a0017925>
- Sliwinski, M. J., Mogle, J. A., Hyun, J., Munoz, E., Smyth, J. M., & Lipton, R. B. (2018). Reliability and Validity of Ambulatory Cognitive Assessments. *Assessment*, *25*(1), 14–30. <https://doi.org/10.1177/1073191116643164>
- Small, B. J., Dixon, R. A., & McArdle, J. J. (2011). Tracking cognition-health changes from 55 to 95 years of age. *The Journals of Gerontology: Series B*, *66B*(S1), 153–161. <https://doi.org/10.1093/geronb/gbq093>
- Smith, M. T., Perlis, M. L., Smith, M. S., Giles, D. E., & Carmody, T. P. (2000). Sleep quality and presleep arousal in chronic pain. *Journal of Behavioral Medicine*, *23*(1), 1–13. <https://doi.org/10.1023/a:1005444719169>
- Snyder, E., Cai, B., DeMuro, C., Morrison, M. F., & Ball, W. (2018). A New Single-Item Sleep Quality Scale: Results of Psychometric Evaluation in Patients With Chronic Primary Insomnia and Depression. *Journal of Clinical Sleep Medicine*, *14*(11), 1849–1857. <https://doi.org/10.5664/jcsm.7478>
- Spira, A. P., Chen-Edinboro, L. P., Wu, M. N., & Yaffe, K. (2014). Impact of sleep on the risk of cognitive decline and dementia. *Current Opinion in Psychiatry*, *27*(6), 478–483. <https://doi.org/10.1097/YCO.000000000000106>
- Stawski, R. S., Scott, S. B., Zawadzki, M. J., Sliwinski, M. J., Marcusson-Clavertz, D., Kim, J., Lanza, S. T., Green, P. A., Almeida, D. M., & Smyth, J. M. (2019). Age differences in everyday stressor-related negative affect: A coordinated analysis. *Psychology and Aging*, *34*(1), 91–105. <https://doi.org/10.1037/pag0000309>
- Steptoe, A., O'Donnell, K., Marmot, M., & Wardle, J. (2008). Positive affect, psychological well-being, and good sleep. *Journal of Psychosomatic Research*, *64*(4), 409–415. <https://doi.org/10.1016/j.jpsychores.2007.11.008>
- Sternberg, D. A., Ballard, K., Hardy, J. L., Katz, B., Doraiswamy, P. M., & Scanlon, M. (2013). The largest human cognitive performance dataset reveals insights into the effects of lifestyle factors and aging. *Frontiers in Human Neuroscience*, *7*, 292. <https://doi.org/10.3389/fnhum.2013.00292>
- Stewart, J. C., Rand, K. L., Hawkins, M. A., & Stines, J. A. (2011). Associations of the shared and unique aspects of positive and negative emotional factors with sleep quality. *Personality and Individual Differences*, *50*(5), 609–614. <https://doi.org/10.1016/j.paid.2010.12.004>

- Stone, A. A., Obbarius, A., Junghaenel, D. U., Wen, C. K. F., & Schneider, S. (2021). High-resolution, field approaches for assessing pain: Ecological Momentary Assessment. *Pain, 162*(1), 4–9. <https://doi.org/10.1097/j.pain.0000000000002049>
- Strand, E. B., Zautra, A. J., Thoresen, M., Ødegård, S., Uhlig, T., & Finset, A. (2006). Positive affect as a factor of resilience in the pain-negative affect relationship in patients with rheumatoid arthritis. *Journal of Psychosomatic Research, 60*(5), 477–484. <https://doi.org/10.1016/j.jpsychores.2005.08.010>
- Sun, Y [Yankun], Le Shi, Bao, Y., Sun, Y [Yan], Shi, J., & Lu, L. (2018). The bidirectional relationship between sleep duration and depression in community-dwelling middle-aged and elderly individuals: Evidence from a longitudinal study. *Sleep Medicine, 52*, 221–229. <https://doi.org/10.1016/j.sleep.2018.03.011>
- Tang, N. K. Y., Goodchild, C. E., Sanborn, A. N., Howard, J., & Salkovskis, P. M. (2012). Deciphering the temporal link between pain and sleep in a heterogeneous chronic pain patient sample: A multilevel daily process study. *Sleep, 35*(5), 675–687A. <https://doi.org/10.5665/sleep.1830>
- Tang, N. K. Y., & Harvey, A. G. (2004). Effects of cognitive arousal and physiological arousal on sleep perception. *Sleep, 27*(1), 69–78. <https://doi.org/10.1093/sleep/27.1.69>
- Tang, N. K. Y., Salkovskis, P. M., Hodges, A., Wright, K. J., Hanna, M., & Hester, J. (2008). Effects of mood on pain responses and pain tolerance: An experimental study in chronic back pain patients. *Pain, 138*(2), 392–401. <https://doi.org/10.1016/j.pain.2008.01.018>
- Tardy, M., Gonthier, R., Barthelemy, J.-C., Roche, F., & Crawford-Achour, E. (2015). Subjective sleep and cognitive complaints in 65 year old subjects: A significant association. The PROOF cohort. *The Journal of Nutrition, Health & Aging, 19*(4), 424–430. <https://doi.org/10.1007/s12603-014-0547-8>
- Teas, E., & Friedman, E. (2021). Sleep and functional capacity in adults: Cross-sectional associations among self-report and objective assessments. *Sleep Health, 7*(2), 198–204. <https://doi.org/10.1016/j.sleh.2020.12.001>
- Terán-Pérez, G. J., Ruiz-Contreras, A. E., González-Robles, R. O., Tarrago-Castellanos, R., Mercadillo, R. E., Jiménez-Anguiano, A., & Velázquez-Moctezuma, J. (2012). Sleep deprivation affects working memory in low but not in high complexity for the n-back test. *Neuroscience and Medicine, 3*(4), 380–386. <https://doi.org/10.4236/nm.2012.34047>
- Thomsen, D. K., Yung Mehlsen, M., Christensen, S., & Zachariae, R. (2003). Rumination—relationship with negative mood and sleep quality. *Personality and Individual Differences, 34*(7), 1293–1301. [https://doi.org/10.1016/S0191-8869\(02\)00120-4](https://doi.org/10.1016/S0191-8869(02)00120-4)



- Tomaso, C. C., Johnson, A. B., & Nelson, T. D. (2021). The effect of sleep deprivation and restriction on mood, emotion, and emotion regulation: Three meta-analyses in one. *Sleep*, 44(6). <https://doi.org/10.1093/sleep/zsaa289>
- Torossian, M., Fiske, S. M., & Jacelon, C. S. (2021). Sleep, mild cognitive impairment, and interventions for sleep improvement: An integrative review. *Western Journal of Nursing Research*, 43(11), 1051-1060. <https://doi.org/10.1177/0193945920986907>
- Tousignant, O. H., Taylor, N. D., Suvak, M. K., & Fireman, G. D. (2019). Effects of rumination and worry on sleep. *Behavior Therapy*, 50(3), 558-570. <https://doi.org/10.1016/j.beth.2018.09.005>
- Tucker, M., McKinley, S., & Stickgold, R. (2011). Sleep optimizes motor skill in older adults. *Journal of the American Geriatrics Society*, 59(4), 603-609. <https://doi.org/10.1111/j.1532-5415.2011.03324.x>
- Uchino, B. N., Berg, C. A., Smith, T. W., Pearce, G., & Skinner, M. (2006). Age-related differences in ambulatory blood pressure during daily stress: Evidence for greater blood pressure reactivity with age. *Psychology and Aging*, 21(2), 231-239. <https://doi.org/10.1037/0882-7974.21.2.231>
- Urtamo, A., Jyväkorpi, S. K., & Strandberg, T. E. (2019). Definitions of successful ageing: A brief review of a multidimensional concept. *Acta Bio-Medica*, 90(2), 359-363. <https://doi.org/10.23750/abm.v90i2.8376>
- Valrie, C. R., Gil, K. M., Redding-Lallinger, R., & Daeschner, C. (2008). Daily mood as a mediator or moderator of the pain-sleep relationship in children with sickle cell disease. *Journal of Pediatric Psychology*, 33(3), 317-322. <https://doi.org/10.1093/jpepsy/jsm058>
- van Dongen, H. P. A., Maislin, G., Mullington, J. M., & Dinges, D. F. (2003). The cumulative cost of additional wakefulness: Dose-response effects on neurobehavioral functions and sleep physiology from chronic sleep restriction and total sleep deprivation. *Sleep*, 26(2), 117-126. <https://doi.org/10.1093/sleep/26.2.117>
- Vandekerckhove, M., Kestemont, J., Weiss, R., Schotte, C., Exadaktylos, V., Haex, B., Verbraecken, J., & Gross, J. J. (2012). Experiential versus analytical emotion regulation and sleep: Breaking the link between negative events and sleep disturbance. *Emotion*, 12(6), 1415-1421. <https://doi.org/10.1037/a0028501>
- Vandekerckhove, M., & Wang, Y. (2018). Emotion, emotion regulation and sleep: An intimate relationship. *AIMS Neuroscience*, 5(1), 1-17. <https://doi.org/10.3934/Neuroscience.2018.1.1>
- Verhaegen, P., Borchelt, M., & Smith, J. (2003). Relation between cardiovascular and metabolic disease and cognition in very old age: Cross-sectional and longitudinal findings from the

- berlin aging study. *Health Psychology*, 22(6), 559–569. <https://doi.org/10.1037/0278-6133.22.6.559>
- Verhaeghen, P. (2018). Working memory and cognitive aging. In B. Knight (Ed.), *Oxford Research Encyclopedia of Psychology*. Oxford University Press.  
<https://doi.org/10.1093/acrefore/9780190236557.013.382>
- Vgontzas, A. N., Zoumakis, M., Bixler, E. O., Lin, H.-M., Prolo, P., Vela-Bueno, A., Kales, A., & Chrousos, G. P. (2003). Impaired nighttime sleep in healthy old versus young adults is associated with elevated plasma interleukin-6 and cortisol levels: Physiologic and therapeutic implications. *The Journal of Clinical Endocrinology & Metabolism*, 88(5), 2087–2095. <https://doi.org/10.1210/jc.2002-021176>
- Villafuerte, G., Miguel-Puga, A., Rodríguez, E. M., Machado, S., Manjarrez, E., & Arias-Carrión, O. (2015). Sleep deprivation and oxidative stress in animal models: A systematic review. *Oxidative Medicine and Cellular Longevity*, 2015, 234952.  
<https://doi.org/10.1155/2015/234952>
- Walker, M. P., & Stickgold, R. (2006). Sleep, memory, and plasticity. *Annual Review of Psychology*, 57, 139–166. <https://doi.org/10.1146/annurev.psych.56.091103.070307>
- Wang, S., Wu, Y., Ungvari, G. S., Ng, C. H., Forester, B. P., Gatchel, J. R., Chiu, H. F. K., Kou, C., Fu, Y., Qi, Y., Yu, Y., Li, B., & Xiang, Y.-T. (2017). Sleep duration and its association with demographics, lifestyle factors, poor mental health and chronic diseases in older Chinese adults. *Psychiatry Research*, 257, 212–218. <https://doi.org/10.1016/j.psychres.2017.07.036>
- Watling, J., Pawlik, B., Scott, K., Booth, S., & Short, M. A. (2017). Sleep loss and affective functioning: More than just mood. *Behavioral Sleep Medicine*, 15(5), 394–409.  
<https://doi.org/10.1080/15402002.2016.1141770>
- Weber, C., Quintus, M., Egloff, B., Luong, G., Riediger, M., & Wrzus, C. (2020). Same old, same old? Age differences in the diversity of daily life. *Psychology and Aging*, 35(3), 434–448.  
<https://doi.org/10.1037/pag0000407>
- Wennberg, A. M. V., Wu, M. N., Rosenberg, P. B., & Spira, A. P. (2017). Sleep disturbance, cognitive decline, and dementia: A review. *Seminars in Neurology*, 37(4), 395–406.  
<https://doi.org/10.1055/s-0037-1604351>
- Whibley, D., Braley, T. J., Kratz, A. L., & Murphy, S. L. (2019). Transient effects of sleep on next-day pain and fatigue in older adults with symptomatic osteoarthritis. *The Journal of Pain*, 20(11), 1373–1382. <https://doi.org/10.1016/j.jpain.2019.04.011>
- Wild, C. J., Nichols, E. S., Battista, M. E., Stojanoski, B., & Owen, A. M. (2018). Dissociable effects of self-reported daily sleep duration on high-level cognitive abilities. *Sleep*, 41(12).  
<https://doi.org/10.1093/sleep/zsy182>

- Winter, L., Lawton, M. P., Langston, C. A., Ruckdeschel, K., & Sando, R. (2007). Symptoms, affects, and self-rated health. *Journal of Aging and Health, 19*(3), 453–469. <https://doi.org/10.1177/0898264307300167>
- Wolff, J. K., Brose, A., Lövdén, M., Tesch-Römer, C., Lindenberger, U., & Schmiedek, F. (2012). Health is health is health? Age differences in intraindividual variability and in within-person versus between-person factor structures of self-reported health complaints. *Psychology and Aging, 27*(4), 881–891. <https://doi.org/10.1037/a0029125>
- Wrzus, C., Luong, G., Wagner, G. G., & Riediger, M. (2015). Can't get it out of my head: Age differences in affective responsiveness vary with preoccupation and elapsed time after daily hassles. *Emotion, 15*(2), 257–269. <https://doi.org/10.1037/emo0000019>
- Wrzus, C., Müller, V., Wagner, G. G., Lindenberger, U., & Riediger, M. (2013). Affective and cardiovascular responding to unpleasant events from adolescence to old age: Complexity of events matters. *Developmental Psychology, 49*(2), 384–397. <https://doi.org/10.1037/a0028325>
- Wrzus, C., Wagner, G. G., & Riediger, M. (2014). Feeling good when sleeping in? Day-to-day associations between sleep duration and affective well-being differ from youth to old age. *Emotion, 14*(3), 624–628. <https://doi.org/10.1037/a0035349>
- Xu, R. (2003). Measuring explained variation in linear mixed effects models. *Statistics in Medicine, 22*(22), 3527–3541. <https://doi.org/10.1002/sim.1572>
- Yang, J., & Kershaw, K. N. (2022). Feasibility of using ecological momentary assessment and continuous heart rate monitoring to measure stress reactivity in natural settings. *PLOS ONE, 17*(3), e0264200. <https://doi.org/10.1371/journal.pone.0264200>
- Yang, L., Krampe, R. T., & Baltes, P. B. (2006). Basic forms of cognitive plasticity extended into the oldest-old: Retest learning, age, and cognitive functioning. *Psychology and Aging, 21*(2), 372–378. <https://doi.org/10.1037/0882-7974.21.2.372>
- Yap, Y., Slavish, D. C., Taylor, D. J., Bei, B., & Wiley, J. F. (2020). Bi-directional relations between stress and self-reported and actigraphy-assessed sleep: A daily intensive longitudinal study. *Sleep, 43*(3), zsz250. <https://doi.org/10.1093/sleep/zsz250>
- Yoo, S.-S., Gujar, N., Hu, P., Jolesz, F. A., & Walker, M. P. (2007). The human emotional brain without sleep--a prefrontal amygdala disconnect. *Current Biology, 17*(20), R877-8. <https://doi.org/10.1016/j.cub.2007.08.007>
- Zavec, Z., Nagy, T., Galkó, A., Nemeth, D., & Janacsek, K. (2020). The relationship between subjective sleep quality and cognitive performance in healthy young adults: Evidence from three empirical studies. *Scientific Reports, 10*(1), 4855. <https://doi.org/10.1038/s41598-020-61627-6>

- Zhang, J., Lam, S.-P., Li, S. X., Tang, N. L., Yu, M. W., Li, A. M., & Wing, Y.-K. (2012). Insomnia, sleep quality, pain, and somatic symptoms: Sex differences and shared genetic components. *Pain, 153*(3), 666–673. <https://doi.org/10.1016/j.pain.2011.12.003>
- Zhang, Z., Xiao, X., Ma, W., & Li, J. (2020). Napping in older adults: A review of current literature. *Current Sleep Medicine Reports, 6*(3), 129–135. <https://doi.org/10.1007/s40675-020-00183-x>
- Zihl, J., Fink, T., Pargent, F., Ziegler, M., & Bühner, M. (2014). Cognitive reserve in young and old healthy subjects: Differences and similarities in a testing-the-limits paradigm with DSST. *PLOS ONE, 9*(1), e84590. <https://doi.org/10.1371/journal.pone.0084590>
- Zinke, K., Noack, H., & Born, J. (2018). Sleep augments training-induced improvement in working memory in children and adults. *Neurobiology of Learning and Memory, 147*, 46–53. <https://doi.org/10.1016/j.nlm.2017.11.009>
- Zinke, K., Zeintl, M., Rose, N. S., Putzmann, J., Pydde, A., & Kliegel, M. (2014). Working memory training and transfer in older adults: Effects of age, baseline performance, and training gains. *Developmental Psychology, 50*(1), 304–315. <https://doi.org/10.1037/a0032982>
- Zinkhan, M., Berger, K., Hense, S., Nagel, M., Obst, A., Koch, B., Penzel, T., Fietze, I., Ahrens, W., Young, P., Happe, S., Kantelhardt, J. W., Kluttig, A., Schmidt-Pokrzywniak, A., Pillmann, F., & Stang, A. (2014). Agreement of different methods for assessing sleep characteristics: A comparison of two actigraphs, wrist and hip placement, and self-report with polysomnography. *Sleep Medicine, 15*(9), 1107–1114. <https://doi.org/10.1016/j.sleep.2014.04.015>
- Zohar, D., Tzischinsky, O., Epstein, R., & Lavie, P. (2005). The effects of sleep loss on medical residents' emotional reactions to work events: A cognitive-energy model. *Sleep, 28*(1), 47–54. <https://doi.org/10.1093/sleep/28.1.47>
- Zung, W. W. K. (1965). A self-rating depression scale. *Archives of General Psychiatry, 12*(1), 63–70. <https://doi.org/10.1001/archpsyc.1965.01720310065008>

## Appendix A

## Model Results on Associations Between Sleep Duration and Affective Functioning

Table A1

Results from Three-Level Models: Sleep Duration Predicting Reactivity and Baseline Negative Affect (NA).

	Estimate	95% CI
<b>Fixed effects</b>		
Intercept NA	<b>9.519</b>	[8.313, 10.707]
Reactivity (NA predicted by stress)	<b>9.244</b>	[8.163, 10.303]
Reactivity predicted by sleep duration <sup>a</sup>	0.070	[-0.739, 0.92]
NA predicted by sleep duration <sup>a</sup>	<b>-0.427</b>	[-0.723, -0.129]
<i>Age and Sample as Moderators</i>		
Intercept NA predicted by age	<b>0.397</b>	[0.235, 0.559]
Intercept NA predicted by sample	1.834	[-0.552, 4.247]
Reactivity predicted by age	-0.094	[-0.234, 0.047]
Reactivity predicted by sample	1.698	[-0.411, 3.883]
Reactivity predicted by sleep duration x age	0.044	[-0.071, 0.155]
Reactivity predicted by sleep duration x sample	0.076	[-1.565, 1.676]
NA predicted by sleep duration x age	-0.017	[-0.058, 0.024]
NA predicted by sleep duration x sample	0.523	[-0.051, 1.115]
<b>Random effects (Variances)</b>		
<i>Within Person, Within Days</i>		
NA residual variance	72.860	[70.725, 75.089]
<i>Within Person, Between Days</i>		
NA residual variance	6.203	[4.674, 7.929]
Reactivity residual variance	77.902	[66.775, 90.679]
<i>Between Person</i>		
NA residual variance	116.352	[99.013, 137.588]
Reactivity residual variance	47.604	[34.465, 63.503]
Reactivity predicted by sleep duration residual variance	3.983	[0.473, 10.701]
NA predicted by sleep duration residual variance	1.044	[0.359, 1.932]

Note. NA = negative affect. CI = credible interval. N<sub>Level1</sub> = 11752, N<sub>Level2</sub> = 2220, N<sub>Level3</sub> = 324.

<sup>a</sup>Sleep duration was person-mean centered.

**Bold faced** estimates indicate that the CI does not cover 0. Because variances can never be estimated at or below zero in Bayesian analysis in Mplus we did not bold face variance estimates.

**Table A2**

*Results from Three-Level Models: Sleep Quality and Sleep Duration Predicting Reactivity and Baseline Negative Affect (NA).*

	Estimate	95% CI
<b>Fixed effects</b>		
Intercept NA	<b>11.872</b>	[10.212, 13.478]
Reactivity (NA predicted by stress)	<b>10.287</b>	[7.731, 13.161]
Reactivity predicted by sleep quality <sup>a</sup>	-0.016	[-0.057, 0.019]
NA predicted by sleep quality <sup>a</sup>	<b>-0.032</b>	[-0.049, -0.015]
Reactivity predicted by sleep duration <sup>a</sup>	0.182	[-0.758, 1.134]
NA predicted by sleep duration <sup>a</sup>	-0.168	[-0.494, 0.15]
<i>Age and Sample as Moderators</i>		
Intercept NA predicted by age	<b>0.427</b>	[0.216, 0.638]
Intercept NA predicted by sample	1.716	[-1.559, 4.908]
Reactivity predicted by age	-0.210	[-0.534, 0.117]
Reactivity predicted by sample	-2.246	[-7.477, 4.052]
Reactivity predicted by sleep quality x age	0.002	[-0.003, 0.006]
Reactivity predicted by sleep quality x sample	0.059	[-0.029, 0.129]
Reactivity predicted by sleep duration x age	0.025	[-0.092, 0.149]
Reactivity predicted by sleep duration x sample	-0.516	[-2.391, 1.405]
NA predicted by sleep quality x age	0.000	[-0.003, 0.002]
NA predicted by sleep quality x sample	0.005	[-0.029, 0.038]
NA predicted by sleep duration x age	-0.007	[-0.055, 0.039]
NA predicted by sleep duration x sample	0.500	[-0.159, 1.166]
<b>Random effects (Variances)</b>		
<i>Within Person, Within Days</i>		
NA residual variance	72.915	[70.796, 75.166]
<i>Within Person, Between Days</i>		
NA residual variance	4.989	[3.491, 6.773]
Reactivity residual variance	77.437	[66.484, 90.127]
<i>Between Person</i>		
NA residual variance	108.705	[90.771, 131.064]
Reactivity residual variance	38.561	[22.301, 55.58]
Reactivity predicted by sleep quality residual variance	0.002	[0.001, 0.005]
NA predicted by sleep quality residual variance	0.003	[0.001, 0.005]
Reactivity predicted by sleep duration residual variance	4.611	[1.099, 13.127]
NA predicted by sleep duration residual variance	1.056	[0.414, 1.98]

Note. NA = negative affect. CI = credible interval.  $N_{\text{Level1}} = 11738$ ,  $N_{\text{Level2}} = 2217$ ,  $N_{\text{Level3}} = 324$ .

<sup>a</sup>Sleep quality and duration were person-mean centered.

**Bold faced** estimates indicate that the CI does not cover 0. Because variances can never be estimated at or below zero in Bayesian analysis in Mplus we did not bold face variance estimates.

**Table A3**

*Results from Two-Level Models: Reactivity, Negative Affect (NA), and Stress Predicting Sleep Duration.*

	Estimate	95% CI
<b>Fixed effects</b>		
Intercept sleep duration	<b>6.753</b>	[6.646, 6.859]
Sleep duration predicted by reactivity <sup>a</sup>	-0.004	[-0.014, 0.006]
Sleep duration predicted by NA <sup>a</sup>	0.039	[-0.003, 0.082]
Sleep duration predicted by stress <sup>a</sup>	-0.007	[-0.018, 0.003]
<i>Age and sample as Moderators</i>		
Intercept sleep duration predicted by age	-0.001	[-0.015, 0.014]
Intercept sleep duration predicted by sample	-0.050	[-0.264, 0.163]
Sleep duration predicted by reactivity x age	0.001	[0.000, 0.003]
Sleep duration predicted by reactivity x sample	0.000	[-0.020, 0.020]
Sleep duration predicted by NA x age	-0.004	[-0.009, 0.001]
Sleep duration predicted by NA x sample	0.013	[-0.072, 0.094]
Sleep duration predicted by stress x age	0.002	[0.000, 0.003]
Sleep duration predicted by stress x sample	0.009	[-0.012, 0.029]
<b>Random Effects (Variances)</b>		
<i>Within Person, Between Days</i>		
Intercept sleep duration residual variance	0.742	[0.687, 0.801]
<i>Between Person</i>		
Intercept sleep duration residual variance	0.810	[0.678, 0.975]
Sleep duration predicted by reactivity residual variance	0.001	[0.001, 0.002]
Sleep duration predicted by NA residual variance	0.010	[0.001, 0.026]
Sleep duration predicted by stress residual variance	0.001	[0.001, 0.002]

*Note.* NA = negative affect. CI = credible interval.  $N_{\text{Level2}} = 1902$ ,  $N_{\text{Level3}} = 322$ .

<sup>a</sup>These predictors were Level 2 estimates from separate three-level models and are de facto person-mean centered.

**Bold faced** estimates indicate that the CI does not cover 0. Because variances can never be estimated at or below zero in Bayesian analysis in Mplus we did not bold face variance estimates.

**Table A4**

*Results from Two-Level Models: Reactivity, Negative Affect (NA), and Stress Predicting Sleep Quality and Sleep Duration.*

	Estimate	95% CI
<b>Fixed effects</b>		
Intercept SQ	<b>70.178</b>	[68.351, 72.008]
Intercept sleep duration	<b>6.753</b>	[6.645, 6.86]
SQ predicted by reactivity <sup>a</sup>	<b>-0.293</b>	[-0.48, -0.105]
SQ predicted by NA <sup>a</sup>	0.578	[-0.135, 1.351]
SQ predicted by stress <sup>a</sup>	-0.012	[-0.181, 0.155]
Sleep duration predicted by reactivity <sup>a</sup>	-0.005	[-0.015, 0.005]
Sleep duration predicted by NA <sup>a</sup>	0.039	[0.000, 0.078]
Sleep duration predicted by stress <sup>a</sup>	-0.007	[-0.017, 0.003]
<i>Age and sample as Moderators</i>		
Intercept SQ predicted by age	-0.015	[-0.266, 0.235]
Intercept SQ predicted by sample	2.708	[-0.973, 6.38]
Intercept sleep duration predicted by age	-0.001	[-0.015, 0.014]
Intercept sleep duration predicted by sample	-0.051	[-0.263, 0.161]
SQ predicted by reactivity x age	0.016	[-0.009, 0.039]
SQ predicted by reactivity x sample	0.340	[-0.049, 0.743]
Sleep duration predicted by reactivity x age	<b>0.001</b>	[0.000, 0.003]
Sleep duration predicted by reactivity x sample	0.001	[-0.019, 0.022]
SQ predicted by NA x age	<b>0.096</b>	[-0.186, 0.008]
SQ predicted by NA x sample	0.291	[-1.224, 1.764]
Sleep duration predicted by NA x age	-0.004	[-0.009, 0.001]
Sleep duration predicted by NA x sample	0.016	[-0.064, 0.093]
SQ predicted by stress x age	<b>0.031</b>	[0.005, 0.056]
SQ predicted by stress x sample	0.119	[-0.223, 0.493]
Sleep duration predicted by stress x age	<b>0.002</b>	[0.000, 0.003]
Sleep duration predicted by stress x sample	0.008	[-0.013, 0.027]
<b>Random Effects (Variances)</b>		
<i>Within Person, Between Days</i>		
Intercept SQ residual variance	251.177	[233.013, 271.556]
Intercept sleep duration residual variance	0.753	[0.699, 0.812]
<i>Between Person</i>		
Intercept SQ residual variance	236.584	[196.841, 284.892]
Intercept sleep duration residual variance	0.815	[0.683, 0.98]
SQ predicted by reactivity residual variance	0.497	[0.239, 0.861]
SQ predicted by NA residual variance	2.521	[0.466, 6.247]
SQ predicted by stress residual variance	0.059	[0.003, 0.248]
Sleep duration predicted by reactivity residual variance	0.001	[0.001, 0.002]
Sleep duration predicted by NA residual variance	0.005	[0.001, 0.017]
Sleep duration predicted by stress residual variance	0.001	[0.001, 0.002]

*Note.* SQ = sleep quality. NA = negative affect. CI = credible interval.  $N_{\text{Level}2} = 1908$ ,  $N_{\text{Level}3} = 323$ .

<sup>a</sup>These predictors were Level 2 estimates from separate three-level models and are de facto person-mean centered.

**Bold faced** estimates indicate that the CI does not cover 0. Because variances can never be estimated at or below zero in Bayesian analysis in Mplus we did not bold face variance estimates.



## Appendix B

### Model Results on Associations Between Sleep Quality and Affective Functioning

**Table B1**

Between-Person: Sleep Quality Predicting Working-Memory, Learning, and Variability.

	Estimate	95% CI
Intercept WM	<b>45.735</b>	[41.983, 49.53]
Learning Curve <sup>a</sup>	<b>6.040</b>	[5.148, 6.973]
Variability	<b>5.484</b>	[5.386, 5.581]
Intercept WM with learning	<b>-57.992</b>	[-88.409, -34.546]
WM on sleep quality	0.095	[-0.14, 0.334]
WM on age group	<b>-22.253</b>	[-29.3, -15.088]
Learning on sleep quality	-0.017	[-0.075, 0.04]
Variability on sleep quality	0.005	[-0.002, 0.011]
<b>Random Variances</b>		
WM	500.710	[389.003, 650.871]
Variability	24.567	[17.651, 33.924]
Learning	0.333	[0.257, 0.436]

*Note.* WM = Working-memory, range = 0–100. Variability = Natural logarithm of the within-person residual variance. Sleep = sleep duration in hours. Sleep and age group were centered on their grand-mean. CI = Bayesian credible interval.  $N_{Level1} = 6430$ ,  $N_{Level2} = 160$ .

<sup>a</sup> Learning is conceptualized as the within-person (random) slope of WM regressed on the natural logarithm of the assessment number.

**Bold faced** estimates indicate that the CI does not cover 0. Because variances can never be estimated at or below zero in Bayesian analysis in Mplus we did not bold face variance estimates.

**Table B2**

Between-Person: Sleep Duration and Sleep Quality Predicting Working-Memory, Learning, and Variability.

	Estimate	95% CI
Intercept WM	<b>48.557</b>	[44.35, 52.817]
Learning Curve <sup>a</sup>	<b>5.252</b>	[4.197, 6.3]
Variability	<b>5.474</b>	[5.359, 5.592]
Intercept WM with learning	<b>-51.425</b>	[-79.7, -29.911]
WM on sleep duration	3.508	[-0.369, 7.434]
WM on sleep duration <sup>2</sup>	<b>-2.871</b>	[-5.024, -0.705]
WM on sleep quality	-0.002	[-0.249, 0.245]
WM on age group	-22.368	[-29.349, -15.564]
Learning on sleep	-0.031	[-0.996, 0.915]
Learning on sleep <sup>2</sup>	0.762	[0.232, 1.291]
Learning on sleep quality	-0.012	[-0.073, 0.048]
Variability on sleep	-0.003	[-0.108, 0.103]
Variability on sleep <sup>2</sup>	0.008	[-0.05, 0.067]
Variability on sleep quality	0.005	[-0.002, 0.011]
<b>Random Variances</b>		
WM	462.574	[359.458, 605.754]
Variability	23.251	[16.764, 32.185]
Learning	0.337	[0.259, 0.442]

Note. WM = Working-memory, range = 0–100. Variability = Natural logarithm of the within-person residual variance. Sleep = sleep duration in hours. Sleep and age group were centered on their grand-mean. CI = Bayesian credible interval.  $N_{\text{Level1}} = 6430$ ,  $N_{\text{Level2}} = 160$ .

<sup>a</sup> Learning is conceptualized as the within-person (random) slope of WM regressed on the natural logarithm of the assessment number.

**Bold faced** estimates indicate that the CI does not cover 0. Because variances can never be estimated at or below zero in Bayesian analysis in Mplus we did not bold face variance estimates.

**Table B3**

Within-Person: Variations in Sleep Quality Predicting Variations in Working-Memory.

	Estimate	95% CI
Intercept WM	<b>68.096</b>	[57.857, 79.446]
WM on sleep quality (within person)	0.029	[-0.014, 0.073]
WM on mean sleep quality (between)	-0.268	[-0.543, 0.001]
WM on mean sleep quality x sleep quality	<b>0.004</b>	[0.001, 0.007]
WM on age group	<b>-22.317</b>	[-29.345, -15.327]
Random Variances		
WM within day	262.427	[252.609, 272.721]
WM between day	65.412	[55.143, 77.075]
WM between person	323.483	[247.819, 421.810]
WM on sleep quality	0.007	[0.001, 0.018]

*Note.* WM = Working-memory, range = 0–100. Sleep = sleep duration in hours; within-person, centered on person-mean. Mean Sleep = Person-mean, centered on grand-mean. Age group was centered on the grand-mean. CI = Bayesian credible interval.  $N_{\text{Level1}} = 6369$ ,  $N_{\text{Level2}} = 1097$ ,  $N_{\text{Level3}} = 160$ .

**Bold faced** estimates indicate that the CI does not cover 0. Because variances can never be estimated at or below zero in Bayesian analysis in Mplus we did not bold face variance estimates.

**Table B4**

Within-Person: Variations in Sleep Duration and Sleep Quality Predicting Variations in Working-Memory.

	Estimate	95% CI
Intercept WM	<b>61.378</b>	[56.84, 65.936]
WM on sleep duration (within person)	<b>1.199</b>	[0.127, 2.271]
WM on sleep duration <sup>2</sup> (within person)	-0.321	[-1.025, 0.387]
WM on sleep quality (within person)	-0.004	[-0.053, 0.044]
WM on mean sleep duration (between)	<b>4.317</b>	[1.181, 7.414]
WM on mean sleep quality (between)	-0.409	[-0.710, -0.121]
WM on mean sleep duration x sleep duration	<b>-1.501</b>	[-2.511, -0.508]
WM on mean sleep duration x sleep duration <sup>2</sup>	-0.423	[-0.966, 0.165]
WM on mean sleep quality x sleep quality	<b>0.006</b>	[0.002, 0.009]
WM on age group	<b>-22.331</b>	[-29.178, -15.543]
Random Variances		
WM within day	262.488	[252.690, 272.694]
WM between day	61.942	[51.683, 73.188]
WM between person	309.196	[235.624, 403.928]
WM on sleep duration	6.302	[0.777, 16.474]
WM on sleep duration <sup>2</sup>	0.413	[0.016, 2.701]
WM on sleep quality	0.006	[0.001, 0.017]

Note. WM = Working-memory, range = 0–100. Sleep = sleep duration in hours; within-person, centered on person-mean. Mean Sleep = Person-mean, centered on grand-mean. Age group was centered on the grand-mean. CI = Bayesian credible interval.  $N_{Level1} = 6369$ ,  $N_{Level2} = 1097$ ,  $N_{Level3} = 160$ .

**Bold faced** estimates indicate that the CI does not cover 0. Because variances can never be estimated at or below zero in Bayesian analysis in Mplus we did not bold face variance estimates.

## List of Publications and Personal Contributions

### Chapter 2:

Lücke, A.J., Wrzus, C., Gerstorf, D., Kunzmann, U., Katzorreck, M., Kolodziejczak, K., Ram, N., Hoppmann, C., & Schilling, O.K. (2022). Good Night – Good Day? Bidirectional Links of Daily Sleep Quality with Negative Affect and Stress Reactivity in Old Age. *Psychology and Aging*. <https://doi.org/10.1037/pag0000704>

I collected parts of the data, conceptualized the idea, conducted the analyses, and wrote the original draft of the manuscript. OKS and CW supervised and provided feedback on the manuscript. OKS, DG, and UK acquired funding and provided feedback on the manuscript. MK and KK collected parts of the data and provided feedback on the manuscript. CH provided feedback on the manuscript.

### Chapter 3:

Lücke, A.J., Wrzus, C., Gerstorf, D., Kunzmann, U., Katzorreck, M., Hoppmann, C., & Schilling, O.K. (2022). Bidirectional Links of Daily Sleep Quality and Duration with Pain and Self-Rated Health in Older Adults' Daily Lives. *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences*.

I collected parts of the data, conceptualized the idea, conducted the analyses, and wrote the original draft of the manuscript. OKS and CW supervised and provided feedback on the manuscript. OKS, DG, and UK acquired funding and provided feedback on the manuscript. MK collected parts of the data and provided feedback on the manuscript. CH provided feedback on the manuscript.

### Chapter 4:

Lücke, A. J., Wrzus, C., Gerstorf, D., Kunzmann, U., Katzorreck, M., Schmiedek, F., Hoppmann, C., & Schilling, O. K. (2021). Between-Person and Within-Person Associations of Sleep and Working-Memory in the Everyday Lives of Old and Very Old Adults: Initial Level, Learning, and Variability. *Sleep*, 45(1). <https://doi.org/10.1093/sleep/zsab279>

I collected parts of the data, conceptualized the idea, conducted the analyses, and wrote the original draft of the manuscript. OKS and CW supervised and provided feedback on the manuscript. OKS, DG, and UK acquired funding and provided feedback on the manuscript. MK collected parts of the data and provided feedback on the manuscript. FS and CH provided feedback on the methods and the manuscript.





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**FAKULTÄT FÜR VERHALTENS-  
UND EMPIRISCHE KULTURWISSENSCHAFTEN**

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